THREE EASSYS ON AGRIBUSINESS ECONOMICS AND MANAGEMENT

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THREE EASSYS ON AGRIBUSINESS ECONOMICS AND MANAGEMENT

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This dissertation consists of three chapters that apply state-of-the-art quantitative optimization methods and econometric techniques to analyze relevant, timely, and important questions in the areas of agribusiness economics and agribusiness management. The first chapter studies a farm manager's optimal decision to control an invasive species. The second chapter examines the spatial efficiency of the U.S. broccoli market via a spatial price analysis approach. The third chapter tests the impact of information about product origin on consumer willingness to pay and quality evaluation of three broccoli varieties. This dissertation can help inform stakeholders' decisions concerning food production, distribution, and marketing problems.

BIOGRAPHICAL SKETCH

Xiaoli Fan's primary area of research interest is food and agribusiness management. She applies state-of-the-art quantitative optimization methods and econometric techniques to analyze relevant, timely, and important questions facing modern agriculture and agribusiness. In addition, she also conducts research on other relevant issues in agribusiness and food systems management including the role of consumer preferences, price analysis to assess market performance, and reduction of food waste in food bank networks. Prior to beginning her doctoral studies at Cornell, Xiaoli spent 3 years managing agricultural research projects for Chinese Academy of Agricultural Sciences. Xiaoli obtained her bachelor's and master's degrees in international economics from Wuhan University in China.

For my family,

He, Dad, Mom, and Edmund.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

GENERAL INTRODUCTION

Agribusiness represents a significant component of the national and global economy. Agricultural economists have been studying issues and problems related to agribusiness for a long time, even before the term "agribusiness" appeared. The term "agribusiness" was first coined by Davis and Goldberg (1957) as "the sum total of all operations involved in the production and distribution of food and fiber". As the agribusiness environment is evolving and the methodologies applied to study this area are developing, researchers are also changing the definition of agribusiness. To better clarify the roles of economics and management in agribusiness, following Cook and Chaddad (2000), King et al. (2010) summarized agribusiness-related research and classified them into two sub-areas: agribusiness economics and agribusiness management. Agribusiness economics research generally applies microeconomic theories, approaches, and frameworks to analyze inter-firm coordination problems facing the agribusiness sector. Agribusiness management, on the other hand, usually studies intra-firm decision making problems facing agribusiness managers.

This dissertation consists of three chapters studying several key issues in the agribusiness sector. The first chapter studies the optimal decisions a farm manager should take to control an invasive species infestation. This chapter falls into the category "agribusiness management" because it applies quantitative methods to help farm managers make profit-maximizing decisions. The second chapter examines the spatial market efficiency of the U.S. broccoli sector via a spatial price analysis approach. The third chapter studies the impact of information about product origin on consumer willingness to pay and quality perception of three broccoli varieties. The last two chapters are closely related to the sub-area of “agribusiness economics” as they apply microeconomic methods to study agribusiness problems.

The first chapter of my dissertation is titled “Optimal Monitoring and Controlling of Invasive Species: The Case of Spotted Wing Drosophila in the United States”. Spotted Wing Drosophila (SWD) is an invasive pest with devastating effects on berry and cherry crops. Current SWD management strategies focus mainly on preventive broad-spectrum insecticide sprays. Growers and extension educators are calling for more sustainable strategies to reduce insecticide sprays. To help inform farm managers the optimal SWD monitoring and controlling decisions, I develop a dynamic bioeconomic model to evaluate performance of alternative SWD management strategies at the farm level. I apply this model to a blueberry grower deciding how to best control a SWD infestation. My results can help fruit growers choose economically- and environmentally-sustainable SWD management strategies that reduce reliance on insecticide applications.

In the second chapter, titled “Examining Spatial Efficiency of the United States Fresh Vegetable Market: The Case of Broccoli Expansion on the East Coast”, I turn the attention to the problem of spatial market efficiency of the U.S. fresh vegetable sector and the growing interest in expanding production to different geographic zones in the East Coast. Over the last several decades, the U.S. fresh vegetable production has become increasingly concentrated in California. This geographic concentration can be explained by California’s climatic advantages but fresh vegetables produced in California need to travel long distances to many destination markets. This may result in unintended consequences such as high transaction costs, an important source of market inefficiency. As concerns about concentration of fresh vegetable production in California grow, there is increased interest in expanding fresh vegetable production base across different geographic and climatic zones in the East Coast. However, more production there requires significant efforts in plant breeding, building post-harvest infrastructure, and establishing supply chain networks. These efforts may be warranted if fresh vegetable markets show improvements in spatial market efficiency. In the second chapter, I examine the level of spatial market efficiency, an approach used widely to evaluate market performance. I employ a switching regime model and apply it to the U.S. fresh broccoli sector using weekly price data from broccoli shipping and demand locations spanning the period 2008-2013. The results show that East Coast broccoli markets tend to be more efficient during seasons when East Coast broccoli is available. The findings from this chapter suggest that expanding broccoli production on the East Coast may contribute to improved market efficiency.

In chapter three, titled “Willingness to Pay, Quality Perception, and Local Food: The Case of Broccoli”, I design an economic experiment to examine the impact of information about product origin on consumer willingness to pay and quality perception (i.e., product appearance and taste) of three broccoli varieties. In my analysis, I use a Tobit model to account for the censored nature of the WTP data. My results show that when no origin information is provided, consumers are willing to pay more for the California variety relative to the two New York State (NYS) varieties. Consumers also evaluate both the appearance and the taste of the California variety higher than the two NYS varieties when no information about product origin is provided. However, when information is given that the two NYS varieties are locally-grown, consumers perceive both the appearance and the taste of the two NYS varieties (relative to the California variety) of superior qualities. Their willingness to pay for the two NYS varieties also increases. These results indicate that although consumers may still consider the California broccoli variety as of superior quality, they are willing to pay a price premium when the two new broccoli varieties were promoted as locally-grown.

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CHAPTER 2

OPTIMAL MONITORING AND CONTROLLING OF INVASIVE SPECIES: THE CASE OF SPOTTED WING DROSOPHILA IN THE UNITED STATES

2.1 Introduction

Spotted wing drosophila (SWD, *Drosophila suzukii*), native to eastern Asia, is a devastating pest of soft-skinned fruits that has rapidly expanded its global range in the past decade to include the U.S., Mexico, Europe, Canada and South America (Walsh et al. 2011; Cini, Ioriatti, and Anfora 2012; Depra et al. 2014). While most Drosophila species are considered harmless or nuisance pests because they are only attracted to spoiled and overripe fruit, SWD exhibits a strong preference for ripe or ripening fruit that has market value (Cini, Ioriatti, and Anfora 2012; Asplen et al. 2015). The crops most significantly affected by SWD include blueberries, blackberries, raspberries, strawberries, and cherries. In the U.S. alone, these high-value crops generate nearly $4.5 billion in receipts at the farm gate annually (USDA NASS 2013) and are grown on over 40,000 farms (USDA 2012).

In addition to a preference for commercial fruit crops, SWD exhibits a high reproductive capacity relative to other members of the species. Between 13 and 16 generations can be completed per year and a female can produce up to 350 eggs during its lifespan (Asplen et al. 2015). This high reproductive potential combined with a short generation time-cycle, results in rapid population growth and increased pest pressure during the critical crop-ripening period (Wiman et al. 2014).

The economic impacts resulting from SWD are a growing concern among businesses in the soft-skinned fruit sector. The female SWD has a unique serrated ovipositor which can puncture the skin of healthy fruit and lay its eggs inside. The visible physical damage caused by oviposition and internal larva feeding can cause considerable yield reduction (Goodhue et al. 2011). Controlling for SWD has also increased insecticide use and labor costs associated with pest management. In a 2015 winter survey of 436 fruit growers in the United States, respondents from 31 states estimated crop losses due to SWD at over $133 million, and increases in insecticide costs of between $100 and $300 per acre due to SWD (North Carolina State Cooperative Extension 2016). For small growers, the economic impact of SWD primarily came in the form of yield loss and management costs. For large commercial growers, however, economic impacts may also include rejection of shipments by buyers, who usually have zero tolerance for SWD infested fruit, particularly for the fresh produce market. Detection of infestation in a shipment, even if small, can result in complete rejection of the shipment (Burrack and Bhattarai 2015). Thus, the negative economic impact of SWD infestations can be substantial. Goodhue et al. (2011) assume a damage prevalence of 30% and estimate SWD annual damages of $500 million in fruit-producing regions across the western U.S. Likewise, North Carolina State Cooperative Extension (2016) estimates over $200 million annual losses due to SWD in eastern production regions of the U.S.

Due to the significant economic impact, current SWD management strategies tend to be very conservative, consisting mainly of preventive broad-spectrum insecticide sprays (Van Timmeren and Isaacs 2013; Wiman et al. 2014; Wise, VanWoerkom, and Isaacs 2015; Haye et al. 2016). However, these strategies may not be sustainable given the problems associated with overuse of insecticides in agriculture, including increased insecticide resistance, traces of insecticide in fruit that may render the product unmarketable, and adverse effects of insecticides on the health of both consumers and farm workers (Van Timmeren and Isaacs 2013). Moreover, growers are overspending on insecticide sprays if the applications exceed required amounts (Wise et al. 2014). Therefore, the soft-skinned fruit industry is seeking alternative management strategies to reduce insecticide use.

Industry and research institutions are proposing alternative integrated pest management (IPM) methods to control SWD infestations and to reduce the negative impact caused by broad-spectrum insecticide applications. Current IPM methods include chemical control, monitoring, pruning, sanitation, and biological control. Among these methods, combining monitoring with insecticide applications is an important strategy which can give adequate early warning and avoid unnecessary sprays (Quarles 2015). There are two ways of incorporating monitoring in farm-level SWD management. The first is a monitor-to-initiate spray strategy, in which the grower initiates weekly monitoring at the beginning of the growing season, and starts spraying after the number of SWD caught by monitoring traps reaches or exceeds a predetermined threshold, and then continues weekly sprays for the remainder of the season while stopping monitoring activities. The second strategy is a monitor-to-guide spray strategy, in which the grower monitors weekly throughout the cropping season, and sprays only in weeks when the number of SWD caught by monitoring traps reaches or exceeds a predetermined threshold.

SWD control strategies that incorporate monitoring seem promising, but few growers have included monitoring in their SWD management plans (North Carolina State Extension Service 2016). Currently, monitoring of SWD activity is based on trapping methods available for other pests and for Drosophila species in general, i.e., attractants in baits and lure are not selective (Burrack et al. 2015). Identification requires using a magnifying glass to detect adult SWD. This makes it difficult and time consuming to distinguish SWD from other harmless Drosophila species in the field (Asplen et al. 2015). Thus, pest management relies on partially observed population density. Given the benefits and disadvantages of monitoring strategies, the research questions of this paper include: What strategies are likely to minimize damages due to SWD? What are the factors affecting the relative performance of monitoring strategies vs. insecticide spray-only strategies? An economic analysis addressing these critical questions is complex given the inability of growers to observe the true SWD population as well as the dynamic nature of SWD infestations.

To fill this gap in the literature, we developed a dynamic bioeconomic model of SWD control to identify the cost-minimizing SWD management strategy. We first develop a Bayesian state-space model to represent the population dynamics of SWD. Based on the estimated parameters, we then introduce control variables to the population model and run simulations to evaluate the performance of alternative SWD management strategies. We apply this model to the case of a blueberry grower making decisions to control SWD infestations during a single growing season. The objective function of the model is to minimize the sum of expected damages and management costs. Accordingly, the model takes into account: 1) the economic impacts accruing to SWD infestations; 2) the commercial value of the crop; 3) the alternative strategies available to monitor and control for SWD; and 4) the cost of each strategy.

Overall, we find that the economic impact of SWD control strategies depends on the efficiency of monitoring traps, the efficacy of insecticides, and the action threshold (i.e. the number of SWD caught in monitoring traps that trigger insecticide application). We first evaluate the performance of alternative SWD managing strategies based on the assumption that trapping efficiency is 0.1. This trapping efficiency is relatively low but is representative of the “status quo”. Our results show that including monitoring in SWD managing strategies can (1) help reduce unnecessary insecticide use; and (2) result in lower total costs than the spray-only strategy, when growers choose appropriate action thresholds. Although current trapping efficiency is low, strong national efforts have been made to design better traps and more selective lures to improve the efficiency of monitoring. To help understand how changes in trapping efficiency can affect economic impact due to SWD infestation, we also evaluate the performance of alternative SWD strategies under different trapping efficiencies. Our results indicate that as the efficiency of monitoring traps improves, management strategies which include monitoring are superior to the spray-only strategy. In particular, our results show that monitor-to-initiate spray strategy could be superior to the baseline spray-only strategy under all trapping efficiency levels, if the appropriate threshold to trigger spraying is chosen. Moreover, growers can choose higher action thresholds when monitoring efficiency increases. In addition, our sensitivity analysis shows that monitor-to-initiate spraying strategies have lower total costs than the monitor-to-guide spray strategies when insecticide efficacy is low. However, as insecticide efficacy improves, the more environmentally sustainable monitor-to-guide strategies are preferred. Our results are valuable for growers, extension specialists, and stakeholders to advance their SWD managing strategies. More importantly, our results have important policy implications: efforts to improve trapping efficiency can lead to more rational use of insecticides.

2.2 Literature Review

Since the detection of SWD in the U.S. in 2008, significant research has examined its biology (Cini, Ioriatti, and Anfora 2012; Pfeiffer, Leskey, and Burrack 2012; Burrack et al 2013; Asplen et al. 2015; Wang et al. 2016b) and has recommended alternative management strategies which include chemical control (Beers et al. 2011; Bruck et al. 2011; Van Timmeren and Isaacs 2013), monitoring and sampling (Lee et al. 2012; Burrack et al. 2015), and biological control (Wang et al. 2016a), among others. There are also a few studies analyzing the economic impact of SWD infestation (Bolda, Goodhue, and Zalom 2010; Goodhue et al. 2011). Although the biology and economic impact are relatively well understood, and alternative SWD management strategies have been recommended, ecological-economic or bioeconomic frameworks are needed to guide the optimization of SWD control and help prevent early insecticide resistance. Reducing the rate of pesticide resistance in SWD might be accomplished through monitoring and treatment within an IPM framework. The importance of monitoring has been recognized in invasive species detection and management (Epanchin-Niell et al. 2012; Berec et al. 2015) and natural resource management (White 2000) when the true state of the system can only be partially observed. In the case of SWD, the current available attractants employed for monitoring are not selective for SWD, making it difficult to differentiate SWD from other fruit flies.

Investigators in agricultural and resource economics have developed several frameworks to deal with partial observability. One such approach is modeling the management problem as a Partially Observed Markov Decision Process (POMDP) (Monahan 1982; Haight and Polasky 2010; MacLachlan, Springborn and Fackler 2016). A POMDP is a generalization of the Markov decision process which allows modeling the uncertainty in the state of the underlying Markov process (Monahan 1980). Applications of POMDP include invasive species control (Moore 2008; Haight and Polasky 2010), endangered species management (Tomberlin 2010), decision making by fishermen (Lane 1989), and survey and management of cryptic threatened species (Chadès et al 2008). One of the advantages of POMDP is that it embeds the complexity of imperfect state information in a decision-making framework. However, because of its computational complexity, this method has the drawback of handling only small state-spaces and representing simplistic problems (Fackler and Haight 2014).

Adaptive decision-making or adaptive management (AM) is another approach that is appropriate to model a partially observed population (White 2000; Williams

2011; MacLachlan, Springborn, and Fackler 2015). Following this approach, a decision-maker simultaneously manages and learns about the possible states of the population through learning-by-doing. AM applications include wetlands management (Williams 2011), invasive species control (Moore 2008), pest management and weed control (Shea et al. 2002), habitat restoration (McCarthy and Possingham 2007), and harvest management (Hauser and Possingham 2008). While incorporating learning-by-doing is an attractive feature, the AM approach is characterized by difficulties that have yet to be overcome. These difficulties include (1) the treatment of uncertainty over time, (2) the necessary assumption of stationarity of resource dynamics over the management time frame, and (3) the choice of a spatial scale that is consistent with both the decision-making and the ecological processes (Williams and Brown 2016).

Bayesian state-space modeling offers an alternative framework to simultaneously address population uncertainty and partial observability. State-space models, which are most common in ecological research, are partitioned into an underlying process describing the transitions of the true states of the system (e.g., real SWD population) over time and an observed process (e.g., trapped SWD population) that links the observations of the system to the true states. Bayesian state-space modeling has been extensively used by ecologists to study fisheries (McAllister and Kirkwood, 1998; Millar and Meyer 2000; Lewy and Nielsen 2003), conservation (Chaloupka and Balazs 2007), harvest regulation (Walters 1975; Trenkel, Elston and Buckland 2000), animal invasion (Hooten et al. 2007), and animal movements (Jonsen, Flemming, and Myers 2005). Although Bayesian state space model can be used to estimate relatively complex population dynamics to address uncertainties in both the state process and the observation process, it has not been applied to solve decision making problems in invasive species management.

In this paper, we use the case of a SWD infestation to extend the applicability of Bayesian state-space modeling to decision making in invasive species management. We do so by introducing control variables to a Bayesian state-space model and then run simulations to evaluate performance of alternative SWD control strategies. Our paper provides a Bayesian framework to optimally monitor and control an invasive species when the population size of the species can only be partially observed. Our model can be extended and applied to study other disease and pest management problems. In addition, our paper contributes to the literature on the control of the SWD by providing an economic analysis to evaluate optimal SWD managing strategies.

2.3 Model

In this section we first develop a Bayesian state-space model to represent the population dynamics of SWD. We estimate parameters of the population dynamics model using a Bayesian Markov Chain Monte Carlo (MCMC) approach. Based on the estimated parameters, we then introduce control variables to the population model and run simulations to evaluate the performance of 10 alternative management strategies to control the population of SWD.

Population Dynamics

Generally, the quantities of interest (e.g., the population density of a species) in Bayesian state-space models are unknown and evolving over time. Observable variables provide only noisy information about the true population dynamics. State-space models typically consist of two equations which describe: (1) the state process that captures the stochastic dynamics of the unobserved state variables, and (2) the observation process that associates the data at hand to the state variables, which may involve some observation noise. Mathematically:

(1) $N_{t+1} = f(N_t, \theta_1, \epsilon_t)$, the state process, and

(2) $y_t = g(N_t, \theta_2, \omega_t)$, the observation process.

The state process (Equation 1) describes the population dynamics, where N_t is a hidden (not observed) state variable (i.e., population size) at period t, θ_1 is a vector of parameters, and ϵ_t is an *iid* noise process which captures the stochastic dynamics of N_t. The observation process (Equation 2) relates the observation (data) at hand y_t (e.g., abundance index, or observed number of captured individuals) to the state variable N_t through an observation function involving parameters θ_2 and some *iid* observation noise ω_t.

We employ a classical Schaefer (logistic) population function (Equation 3) and assume that the population at each period is not affected by the number of SWD caught in monitoring traps, yielding:

(3) $N_{t+1} = \left\{N_t + r \times N_t \times \left(1 - \frac{N_t}{K}\right)\right\} \times e^{\epsilon_{t+1}}$

where r is the intrinsic population growth rate, K is the carrying capacity of the population, ϵ_{t+1} is a normally distributed ($N(0,\ \sigma^2)$) random term representing environmental noise (e.g., rain, temperature, humidity, etc.).

We assume that the fate of each individual SWD facing a trap (i.e. being captured or escaping) is ruled by the same *Bernoulli* mechanism. Then, the number of captures can be thought of as a binomial sampling drawn from the population. We define the likelihood of y_t conditional on N_t as:

(4) $y_t \sim Binomial(N_t,\ \pi)$

where π is the trapping efficiency, defined as the probability of an adult SWD being captured by monitoring traps.

Going forward, we use brackets to denote probability distributions. Letting $\theta_1 = (r, K, \sigma^2)$, the stochastic transition defined in Equation 3 can be written as:

(5) $[N_{t+1} | N_t, \theta_1]$

Let $t = (1, \ldots, T)$ denote the time series for which observations are available. Conditional on θ_1, the sequence of unknown states $(N_1, \ldots, N_T)$ follows a first-order Markov chain. Assuming an initial value for N_1 and using the transition kernel defined by Equation 5, the prior distribution can be formulated as:

(6) $[(N_1, \ldots, N_T), \theta_1] = [\theta_1] \times [N_1 | \theta_1] \times \prod_{t=1}^{T} [N_{t+1} | N_t, \theta_1]$

Conditional on state N_t and parameter $\theta_2 = \pi$, the likelihood of y_t can be written as:

(7) $[(y_1, \ldots, y_T), \theta_2] = \prod_{t=1}^{T} [y_t | N_t, \theta_2]$

Combining the prior on the parameters $[\theta] = [\theta_1, \theta_2]$, and applying Bayes' rule, the full posterior distribution of all unknowns can be decomposed as:

(8) $[(N_1, \ldots, N_T), \theta | (y_1, \ldots, y_T)] \propto [\theta] \times [N_1] \times \prod_{t=1}^{T} [N_{t+1} | N_t, \theta_1] \times \prod_{t=1}^{T} [y_t | N_t, \theta_2]$

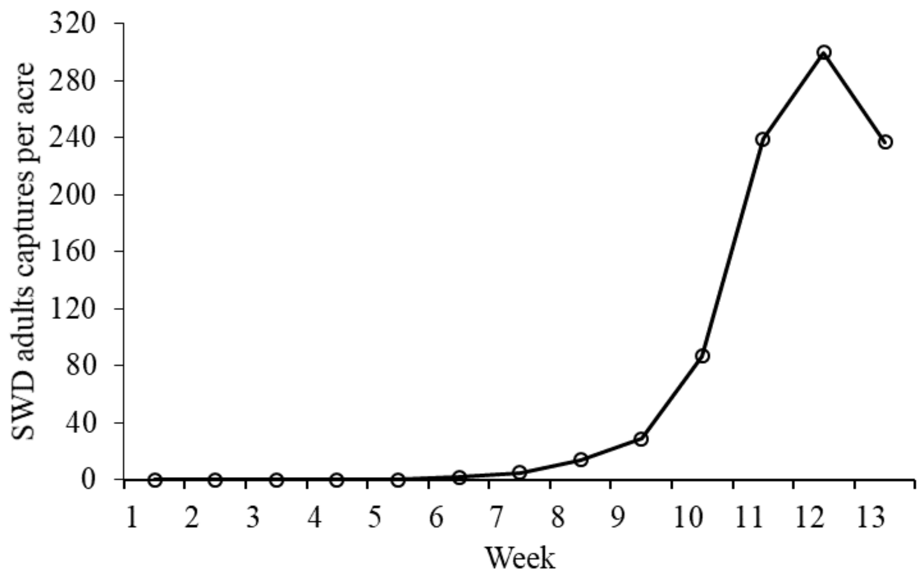


Figure 2.1. Weekly adult SWD trap captures

A sample of the full joint posterior distribution in Equation (8) can be obtained from MCMC sampling using the OpenBUGS software, a commonly used software for performing Bayesian inference (Lunn et al. 2009). The trap data used for the MCMC estimation are presented in figure 2.1. These data were obtained from a blueberry farm located in western New York State. Adult SWD individuals were monitored for 13 weeks in the 2014 growing season, starting from the fruit coloring stage, generally two weeks before harvest starts, and until the harvest ends.

Economic Model

In this section, we explain how we use the results from the population model to test the response of the SWD population levels under alternative management strategies. We develop an economic model for managing SWD infestation based on partial observation of the population level.

Our economic model describes the decision process of a blueberry farm manager controlling SWD infestations (figure 2.2). At the beginning of each period, nature decides the population level and SWD damage, the farm manager then chooses management actions. In each period, the manager makes two decisions. The first decision is whether to monitor the SWD population. We define a binary variable M_t to denote the monitoring decision ($M_t = 1$ if monitoring takes places and 0 otherwise). The second decision is whether to spray insecticide. Let S_t denote the spraying decision (S_t =1 if the farm manger decides to spray at period t and 0 otherwise). Note that the spraying decision may depend on the monitoring results. Following the management actions, the state of the infestation may change and will transition to the next period. Taking into account the effect of control actions, the population transition Equation (3) can be reformulated as:

(9)

$$N_{t+1} = \begin{cases} \left\{(1-Efficacy)\times N_t + r\times(1-Efficacy)\times N_t\times\left(1-\frac{(1-Efficacy)\times N_t}{K}\right)\right\}\times e^{\epsilon_{t+1}}, \text{if} \\ \left\{N_t + r\times N_t\times\left(1-\frac{N_t}{K}\right)\right\}\times e^{\epsilon_{t+1}}, \text{otherwise} \end{cases}$$

where $Efficacy$ denotes the efficacy of the insecticide, which is measured by the percent reduction in SWD population.

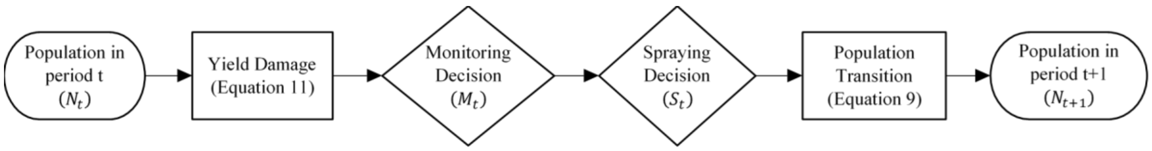


Figure 2.2. Decision process of controlling SWD infestation

The objective of the farm manager is to minimize the sum of expected damages and management costs across time, by choosing an optimal SWD management strategy (δ). The difference between alternative management strategies falls into the two aforementioned control decisions at each period. We formulate the optimal SWD control problem as follows:

(10)

$$\min_{\delta} Total\ Cost(\delta) = \mathbb{E}\left\{\sum_{t=1}^{T} Damage_t\ (N_t(\delta)) + Management\ Cost_t(S_t(\delta) + M_t(\delta))\right\}$$

where $\mathbb{E}$ is the expectation operator over the random quantities due to the stochastic nature of the dynamic system. At each period $\boldsymbol{t}$, the manager faces two types of costs: damages and management costs. We assume that damages depend on the population level at the start of each period and that SWD only cause damage by reducing yields. Let p be the probability that blueberry fruit is damaged by a single SWD. The probability that the fruit is not damaged by SWD at period $\boldsymbol{t}$ is $(1-p)^{N_t}$ and the probability that fruit is damaged by SWD of population size N_t is $1-(1-p)^{N_t}$. The damage for period $\boldsymbol{t}$ is thus the product of weekly blueberry yields, the price of blueberries, and the probability of SWD damage (Equation 11).

(11)

$$Damage_t\,(N_t) = Baseline\ Annual\ Yield \times Weekly\ Relative\ Yield_t \times Price \times \{1-(1-p)^{N_t}\}$$

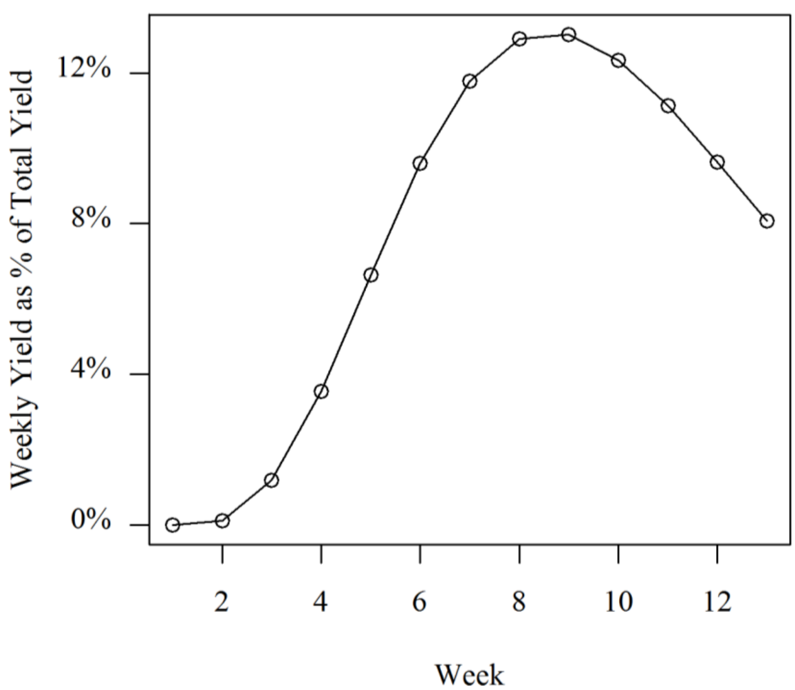


Figure 2.3. Blueberry weekly yield as percentage of total yield

Weekly relative yields (weekly yield as percentage of total yield) are shown in figure 2.3. These yields are approximated by a gamma distribution using data obtained from field observations (Gregory Loeb, personal communication, 2016).

Management costs are the sum of monitoring costs and spraying costs. A grower may have different management costs every week depending on the actual SWD population. For example, the grower could apply different dosages of insecticide every week, which leads to varying spraying costs. However, in reality growers usually follow manufacturers' recommendation to apply a single dosage of insecticide every week. Therefore, we assume a single level of monitoring and spraying costs. Management costs can be expressed as:

$$(12)\ Management\ Cost_t = Unit\ Spraying\ Material\ Cost \times S_t \\ + Unit\ Spraying\ Labor\ Cost \times S_t \\ + Unit\ Monitoring\ Material\ Cost \times M_t \\ + Unit\ Monitoring\ Labor\ Cost \times M_t$$

We design and implement Monte Carlo experiments to evaluate 10 different strategies for managing a SWD infestation in a one-acre blueberry farm. Each experiment consists of 10,000 simulation runs, over a growing season of 13 weeks (the period between fruit coloring and harvest). The 10 alternative strategies can be classified into four categories: no intervention, spray-only, monitor-to-initiate spray and monitor-to-guide spray (table 2.1).

Table 2.1. Alternative SWD Control/Management Strategies

Strategy	Description	Monitor	Spray
No Intervention			
1	Never monitor; Never spray	Never	Never
Baseline Strategy: Spray-only			
2	Spray throughout the Season	Never	Always
Monitor-to-initiate Spray Strategies			
3	Threshold=1 fly per acre	Sometimes	Sometimes
4	Threshold=3 flies per acre	Sometimes	Sometimes
5	Threshold=5 flies per acre	Sometimes	Sometimes
6	Threshold=10 flies per acre	Sometimes	Sometimes
Monitor-to-guide Spray Strategies			
7	Threshold=1 fly per acre	Always	Sometimes
8	Threshold=3 flies per acre	Always	Sometimes
9	Threshold=5 flies per acre	Always	Sometimes
10	Threshold=10 flies per acre	Always	Sometimes

Source: Author's definition of strategies based on extended discussion with extension specialists and industry stakeholders.

The farm manager does not take any control action under the no intervention strategy. The most commonly adopted management strategy by growers is spray-only; we therefore choose this strategy as the baseline to compare outcomes of alternative strategies. Two additional types of sustainable strategies recommended by research and extension professionals are monitor-to-initiate spray strategies and monitor-to-guide spray strategies. For simplicity, we will refer to these two types of strategies as "initiate" strategies and "guide" strategies from here on. Interest in these strategy types

Table 2.2. Parameter Values Used to Calculate Economic Cost

Parameter	Value	Description	Sources
$Efficacy$	0.9	Proportion of SWD killed by insecticide	Provisional mortality rate suggested by Tanigoshi, Spitler and Gerdeman (2016)
p	0.001	Probability blueberry fruit damaged by one individual SWD	Calibrated based on a 50% yield loss if no control action taken
Baseline annual yield	5000	Baseline yield of blueberry (lb./acre)	Harrington and Good (2016)
Price	2.17	Pick your own (PYO) price ($/lb.)	Pritts and Hdidenreich (2016)
Unit spraying material cost	20.84	Material cost of applying insecticide ($/week/acre)	Calculated based on North Carolina State Cooperative Extension (2016) and personal communication with D. Welch, October 28, 2015
Unit spraying labor cost	11.11	Labor cost of applying insecticide ($/week/acre)	Calculated based on North Carolina State Cooperative Extension (2016) and personal communication with D. Welch, October 28, 2015
Unit monitoring material cost	9.3	Weekly cost for materials to set up monitoring traps and lures	J. Carroll, personal communication, April 5, 2016
Unit monitoring labor cost	6	Weekly labor cost to check monitoring traps	J. Carroll, personal communication, April 5, 2016

stems from a desire to avoid unnecessary insecticide application. The difference between these two strategy types is that growers stop monitoring for SWD once they start insecticide sprays under initiate strategies; while under guide strategies, growers monitor SWD throughout the season and only spray if the number of trapped SWD reaches a predetermined threshold. To find the optimal SWD control strategy, we run simulations using the objective function (Equation 10) to rank strategies according to total cost during the season. The model parameters used to run simulations are shown in table 2.2. These parameters are based on the existing literature and on estimates from entomologists and extension personnel (Gregory Loeb and Juliet Carroll, personal communication, 2016).

2.4 Results and Discussion

In this section, we first present the parameter estimates governing population dynamics. We then show the performance of alternative SWD control strategies under different trapping efficiency levels. We also compare the performance of initiate strategies and guide strategies. We finally discuss the robustness of our results with respect to varying insecticide efficacy.

Table 2.3. Descriptive Statistics of the Marginal Posterior Distributions of the Key Parameters

Parameter	Prior Distribution	Posterior Distributions of Key Parameters				
		Mean	Standard Deviation	2.5th Percentile	Median	97.5th Percentile
r	$\sim$ *Uniform*(0.01, 10)	1.11	0.4583	0.3668	1.063	2.144
K	$\sim$ *Uniform*(100, 10000)	3290	1350	1832	2878	7236
σ^2	$\log(\sigma^2)$ $\sim$ *Uniform*(-20, 20)	0.3544	0.3894	0.0678	0.2468	1.272

Source: Authors' estimations.

Population Dynamics

The prior distributions and main statistics of the marginal posterior distributions of the key parameters used in the Bayesian state-space population model are shown in table

2.3. The weekly intrinsic growth rate r, the per capita rate of population growth, is 1.063, which is relatively high and indicates that the population size can grow very quickly without proper management. The posterior median of carrying capacity K is 2,878 flies per acre, indicating the maximum population size of SWD population on a representative one-acre blueberry farm in New York State.

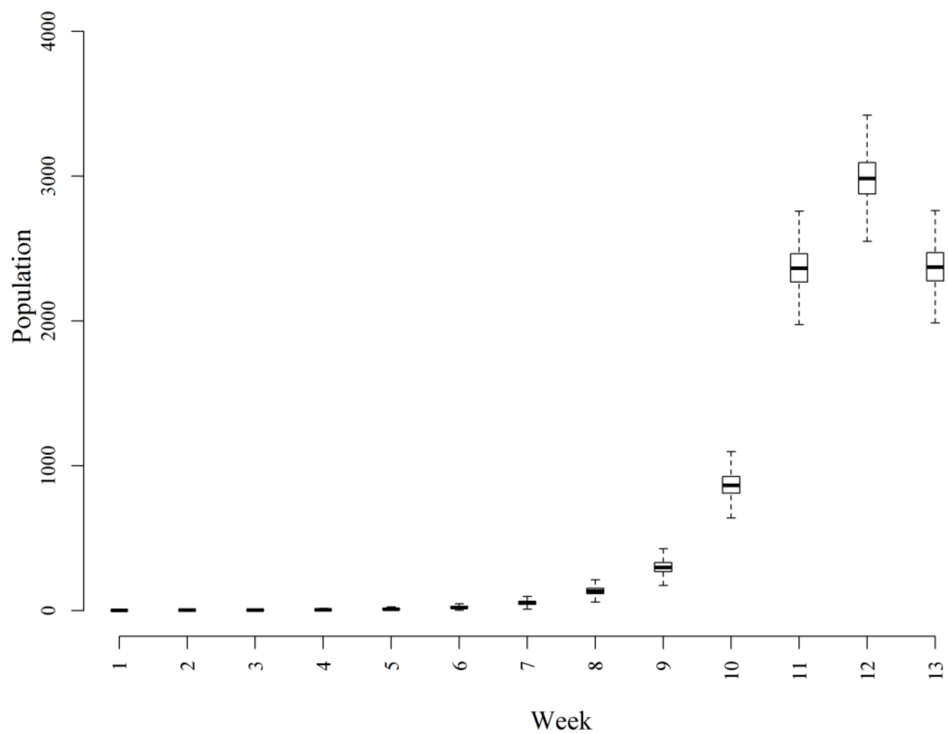


Figure 2.4. Marginal posterior distributions of the estimated SWD population size

The model also provides estimates of the time series of the latent (unobserved) SWD population if the SWD infestation is not controlled (Figure 2.4). The time series of the population size exhibits the typical S-shape of logistic growth curves. From week 1 to 11, the population quickly grows to more than 2,000 flies per acre. Starting in week 11, the population grows at a relatively slower rate and reaches its maximum around 3,000 flies per acre in week 12. The population size then decreases in week 13 to around 2,400 flies per acre, as most fruit has been already harvested.

Performance of Alternative Management Strategies

Simulations over 13 weeks were performed for management strategies 1-10 employing the parameter values described above. Table 2.4 shows the main results when we assume a trapping efficiency of 0.1, which is consistent with the traps currently used by growers. The no intervention strategy has the highest damage and total cost. Under this strategy, growers lose about 46% of the crop and are not able to make a positive profit because the yield loss is so high. The baseline spray-only strategy, which is also the most commonly used strategy, has the lowest damage cost. However, the spraying cost of the baseline strategy is the highest because growers are employing proactive calendar spray programs to prevent the SWD infestation. The initiate strategy has lower total cost than the baseline strategy if the threshold to trigger insecticide spray is $y_t = 1$ fly per acre and has the same total cost as the baseline strategy if the threshold $y_t = 3$ flies per acre is used. This is largely due to the reduction in insecticide applications. Although other initiate strategies using higher thresholds are more expensive than the baseline strategy, these strategies have lower spraying cost and are more environmentally sustainable. The guide strategies generate even lower spraying costs but higher damages. For example, when using $y_t = 10$ flies per acre as a threshold, the damage incurred under the guide strategy is $807, which is more than twice the damage incurred under the initiate strategy ($332).

The results shown in table 2.4 are based on the assumption that trapping efficiency is 0.1. This trapping efficiency is relatively low because the currently available lure/attractants are not selective for SWD, thus making it difficult to differentiate SWD from other harmless fruit flies. Strong national efforts have been made to design better traps and more selective lures to improve the efficiency of monitoring. Trapping efficiency can significantly affect how effectively monitoring traps can capture SWD individuals and in turn affect the grower's spraying decisions and the choice of the action threshold. It is therefore very important to study how the relative performance of alternative SWD management strategies changes with respect to changes in trapping efficiency.

Table 2.4. Estimated Economic Costs of SWD Infestation under Various Management Strategies when Trap Efficiency is 0.1

Strategy	Description	Yield (lbs./acre)	Damage Cost($)	Monitoring Cost ($)	Spraying Cost($)	Total Cost($)	Profit ($/acre)
No SWD Infestation		/	5,000	/	/	/	2,220
No Intervention							
1	Never monitor; Never spray	2,684	5,026	0	0	5,026	-2,807
Baseline Strategy: Spray-only							
2	Spray throughout the season	4,984	35	0	383	419	1,801
Monitor-to-initiate Spray Strategies							
3	Threshold=1 fly per acre	4,983	38	35	341	415	1,805
4	Threshold=3 flies per acre	4,964	79	69	272	419	1,800
5	Threshold=5 flies per acre	4,935	142	82	243	468	1,752
6	Threshold=10 flies per acre	4,847	332	100	207	639	1,580
Monitor-to-guide Spray Strategies							
7	Threshold=1 fly per acre	4962	83	184	166	433	1,787
8	Threshold=3 flies per acre	4888	243	184	99	526	1,694
9	Threshold=5 flies per acre	4808	417	184	90	690	1,530
10	Threshold=10 flies per acre	4628	807	184	79	1,069	1,150

Initiate Strategies

Figure 2.5 shows the percentage change of the total costs of initiate strategies relative to the baseline spray-only strategy under different trapping efficiencies. We find that initiate strategies could be superior to the baseline spray-only strategy under all trapping efficiencies, if growers choose the optimal action threshold to initiate insecticide spray. For instance, the total cost of the initiate strategy is 1.0% lower than the cost of the baseline strategy when trapping efficiency is 0.1, 3.8% lower when trapping efficiency is 0.2, and more than 4% lower when trapping efficiency is equal to or higher than 0.3. These results provide support for the industry's call for growers to adopt the initiate strategy rather than the spray-only strategy.

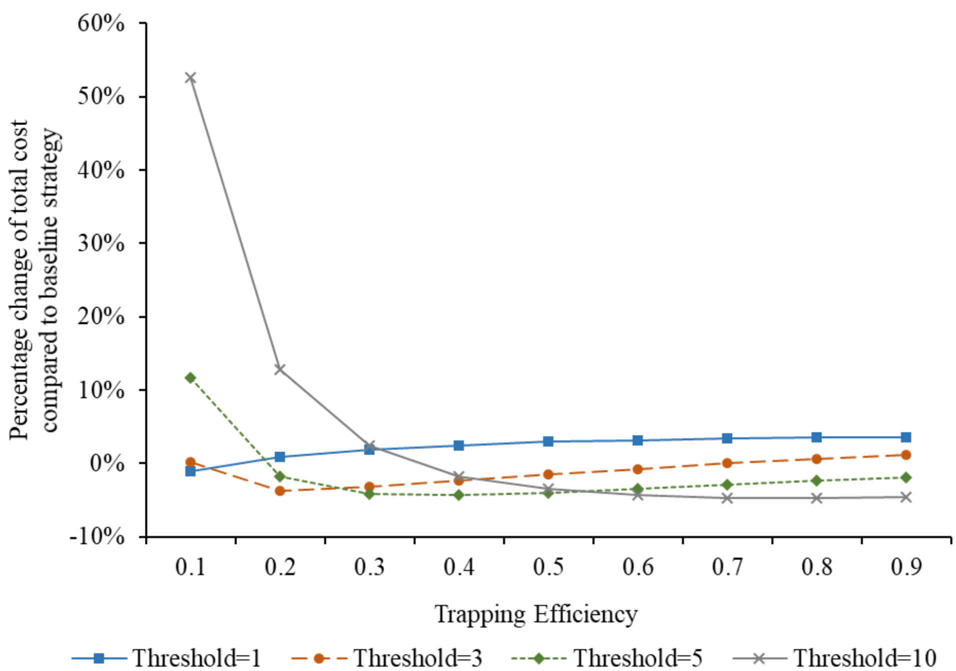


Figure 2.5. Relative total cost of monitor-to-initiate spray strategies vs. baseline spray-only strategy

Our results also suggest that growers' selection of the threshold at which to initiate insecticide spray depend on the trapping efficiency. Growers should use lower thresholds when trapping efficiency is low and switch to higher thresholds as trapping efficiency improves. For example, when trapping efficiency is as low as 0.1, growers should choose the threshold $y_t = 1$ fly per acre for the initiate strategy to be slightly superior to the spray-only strategy (Figure 2.5). Although the profit implications of initiate strategy with threshold $y_t = 1$ fly per acre and the spray-only strategy are practically the same, the former should be preferred given the risk of SWD developing resistance to insecticides. The best strategy is to initiate using the threshold $y_t = 3$ flies per acre when the trapping efficiency improves to 0.2. A threshold of $y_t = 5$ flies per acre should be chosen when the trapping efficiency is between 0.3 and 0.5. The threshold of $y_t = 10$ flies per acre should be selected when the trapping efficiency is 0.6 or more.

Our results provide support for efforts to improve trapping efficiency. More efficient traps will result in lower total costs. In addition, more efficient traps allow growers to use higher action thresholds to initiate insecticide sprays. However, the impact of trapping efficiency improvement on total cost differs depending on the threshold selected. When choosing a low threshold of $y_t = 1$ fly per acre, the relative total cost of the initiate strategy increases as trapping efficiency improves. Under higher thresholds, the total cost of the initiate strategy decreases first and then increases. These different patterns are largely due to trade-offs between spraying cost and damages. Lower thresholds and more efficient traps can result in insecticide sprays being triggered earlier, thus reducing damages but potentially increasing spraying costs. For each action threshold to initiate spraying, there is a certain trapping efficiency where the increases in spraying cost will dominate the decreases in damages beyond that trapping efficiency.

Guide Strategies

The results of guide strategies under different trapping efficiencies are shown in figure 2.6. As trapping efficiency improves, the patterns of the change in relative total cost of the guide strategies are similar to those of the initiate strategies. Nonetheless, unlike the initiate strategies which can be superior to the baseline spray-only strategy under all trapping efficiencies, guide strategies are lower cost than the baseline strategy only when trapping efficiency is above 0.2. When trapping efficiency is 0.1, the guide strategy with the lowest total cost is the one using the threshold of $y_t = 1$ fly per acre, but the total cost of this strategy is 3.4 percent higher than the baseline strategy. The optimal action threshold is $y_t = 3$ flies per acre when trapping efficiency is between 0.2 and 0.4. A threshold of $y_t = 5$ flies per acre is optimal when trapping efficiency is above 0.5. A threshold of $y_t = 10$ flies per acre is never optimal for the guide strategy.

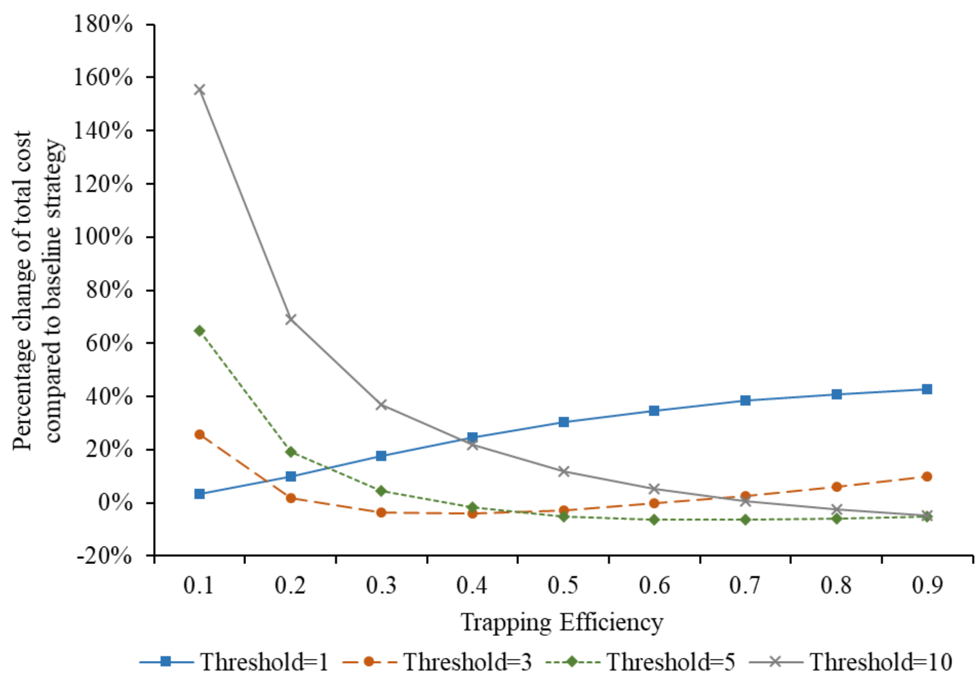
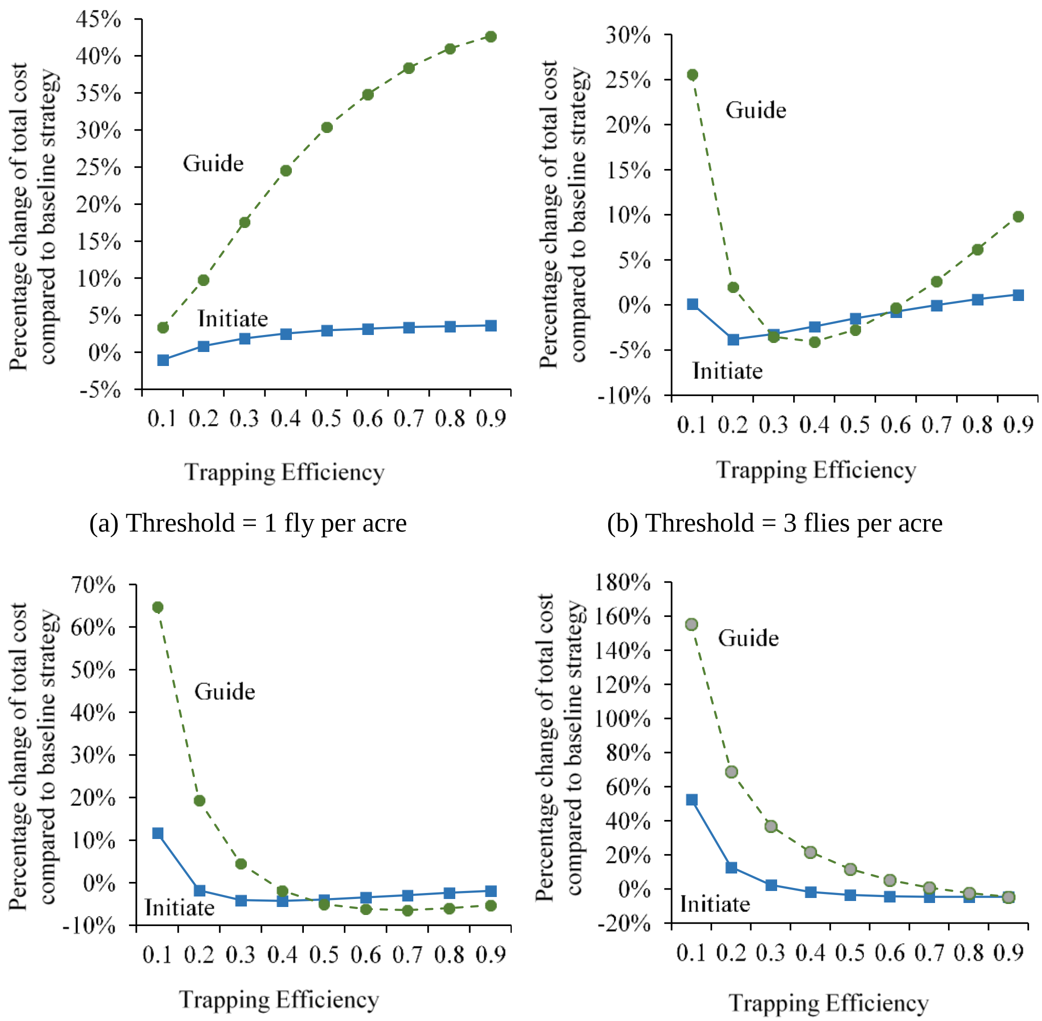


Figure 2.6. Relative total cost of monitor-to-guide spray strategies vs. baseline spray-only strategy

Initiate Strategies vs. Guide Strategies

Although some growers have responded to the industry's call to use monitoring traps to inform their insecticide spray decisions, their choices between monitoring strategies have remained uninformed. Should growers only use monitoring traps to initiate insecticide spray or should they keep monitoring the SWD population levels and apply insecticide only if the trapped number of flies is above a certain action threshold? To answer this question, we compare the performance of these two types of management strategies. Detailed results are shown in figure 2.7.



(a) Threshold = 1 fly per acre

(b) Threshold = 3 flies per acre

(c) Threshold = 5 flies per acre

(d) Threshold = 10 flies per acre

Figure 2.7. Monitor-to-initiate strategy vs. monitor-to-guide strategy

The relative performance of the two types of monitoring strategies depends on the tradeoffs among damage costs, monitoring costs, and spraying costs. As trapping efficiency improves, insecticide application will be triggered earlier and this will lead to higher spraying costs and lower damages costs. This is true for both initiate strategies and guide strategies. However, for guide strategies, monitoring costs remain the same when trapping efficiency improves. But for initiate strategies, monitoring costs decrease as trapping efficiency improves because spraying triggered early also means early termination of monitor activities. The tradeoffs among the three components of costs also depend on the action threshold chosen by growers. When using a very low threshold ($y_t = 1$), the total cost of the guide strategy is higher than the total cost of the initiate strategy (figure 2.7-a). The major reason is that the monitoring cost of guide strategy is much higher than that of initiate strategy. When using a threshold of $y_t = 3$ flies per acre and when trapping efficiency is between 0.3 and 0.5 (figure 2.7-b), or when using a threshold of $y_t = 5$ flies per acre with trapping efficiency above 0.5 (figure 2.7-c), guide strategies yield lower total costs than initiate strategies. For the very high threshold of $y_t = 10$ flies per acre, the initiate strategy always performs better than guide strategy but the relative costs of these two strategies converge as trapping efficiency improves (figure 2.7-d).

Sensitivity Analysis against Insecticide Efficacy

Changing the insecticide efficacy can also change the relative performance of SWD managing strategies. A powerful insecticide can significantly reduce the SWD population such that growers can skip spraying during some periods with only a mild infestation following a high-efficacy spray. Conversely, if the efficacy of the insecticide is so low that growers need to spray every week to minimize damages due to SWD infestation, then growers should not include monitoring in their SWD managing strategies. As we can see in figure 2.8 and figure 2.9, when decreasing insecticide efficacy from 90% to 70%, both the initiate strategy and guide strategy perform worse than the baseline spray-only strategy, regardless of the trapping efficiency. Increasing the insecticide efficacy from 90% to 97%, on the other hand, helps reduce total costs of both initiate and guide strategies (figure 2.10 and figure 2.11). However, the magnitude of reduction in total cost depends on trapping efficiency. With trapping efficiency of 0.1, the total cost of using threshold of $y_t = 10$ flies per acre decreases greatly from 50.6% to 41.9% for the initiate strategy and from 155.4% to 101.6% for the guide strategy. With trapping efficiency of 0.9, the total cost of using $y_t = 10$ flies per acre decreases slightly from -4.6% to -4.8% for initiate strategies and from -4.4% to -8.9% for guide strategy.

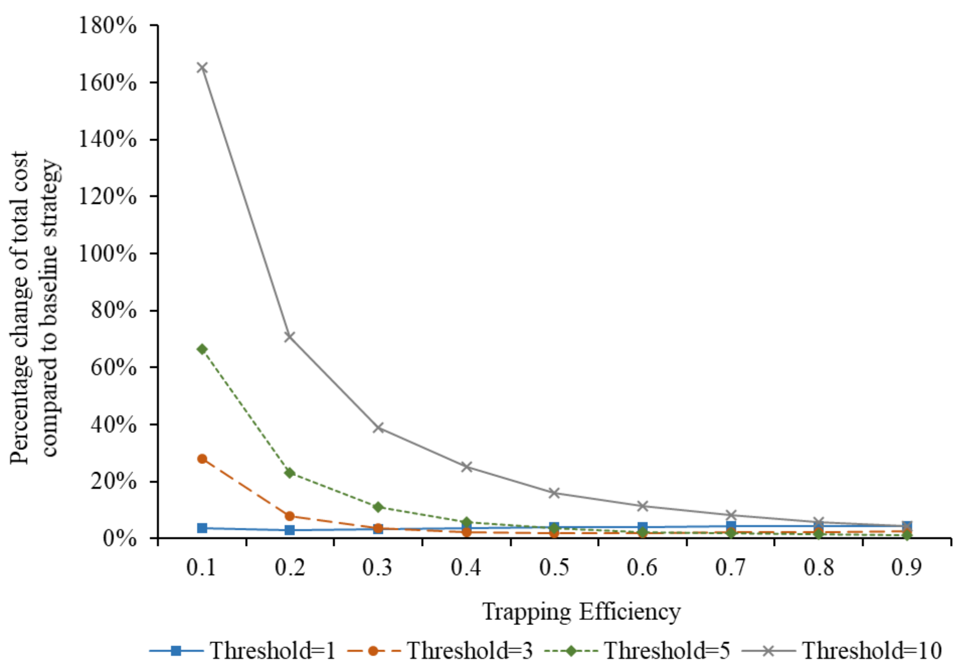


Figure 2.8. Relative total cost of monitor-to-initiate spray strategies using low efficacy (70%) insecticide

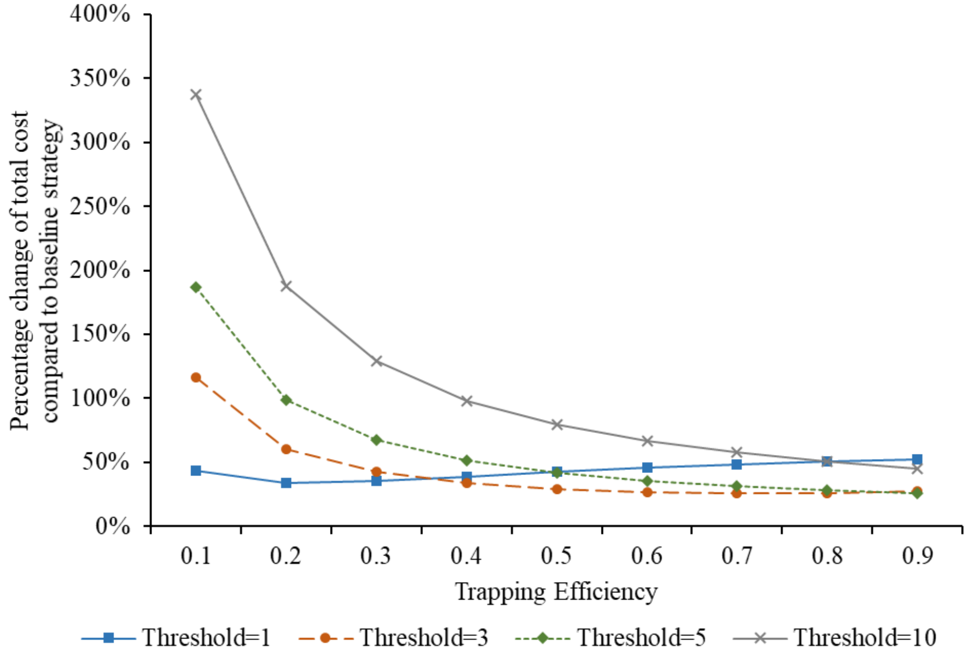


Figure 2.9. Relative total cost of monitor-to-guide spray strategies using low efficacy (70%) insecticide

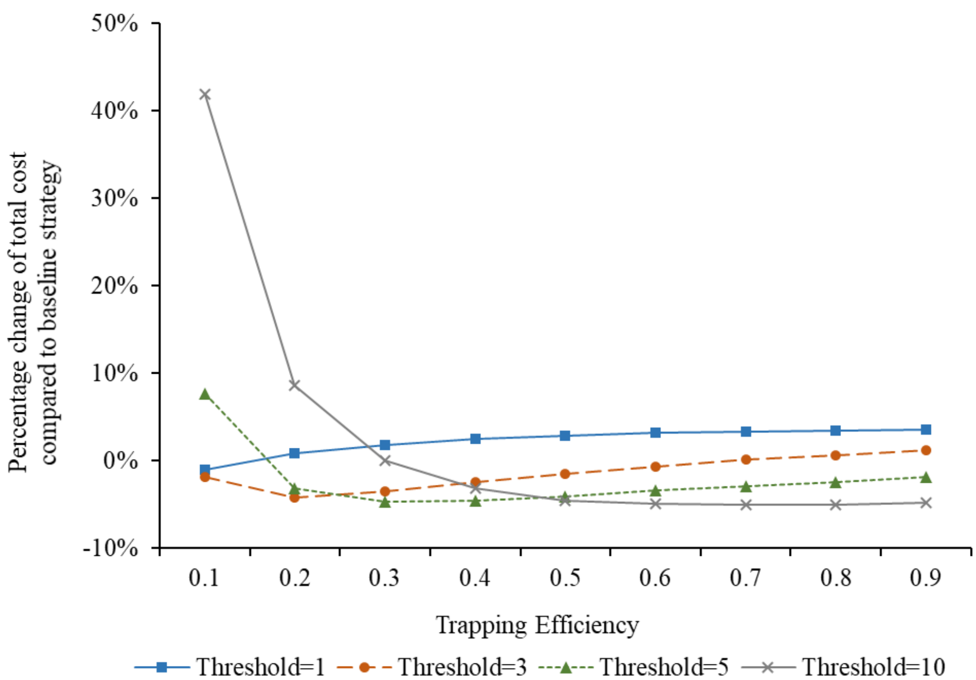


Figure 2.10. Relative total cost of monitor-to-initiate spray strategies using ultra-high efficacy (97%) insecticide

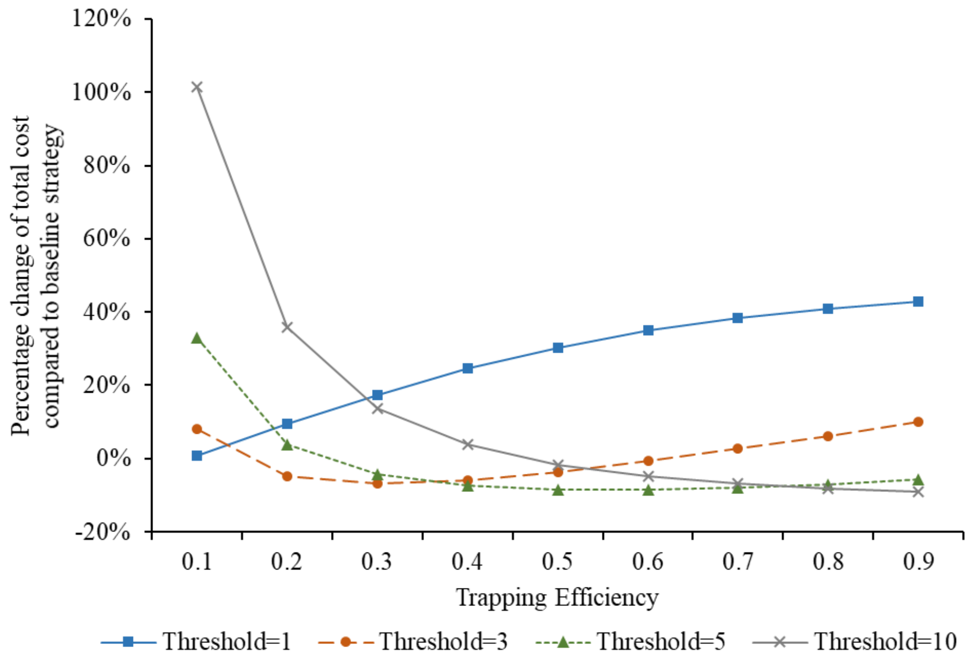
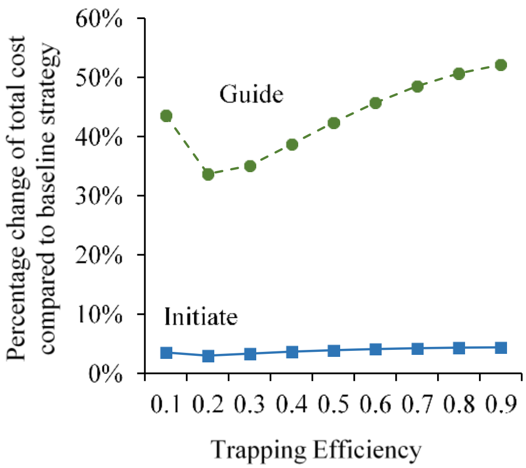
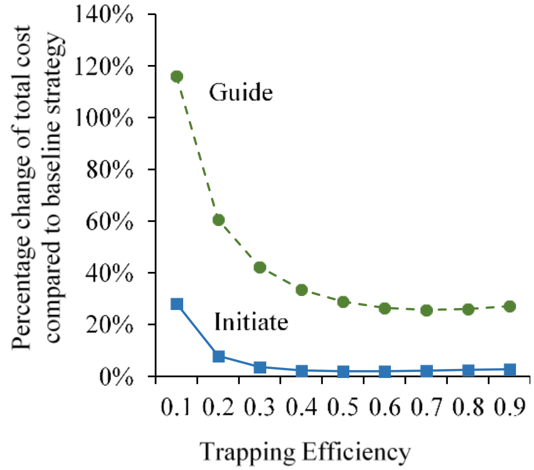


Figure 2.11. Relative total cost of monitor-to-guide spray strategies using ultra-high efficacy (97%) insecticide

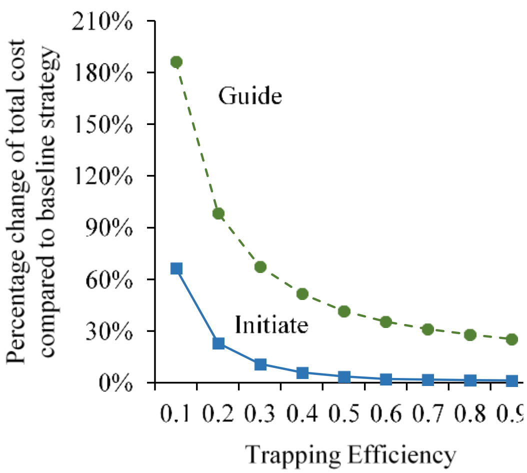
Regarding the relative performance of initiate strategies and guide strategies, we find that guide strategies are more sensitive to changes in insecticide efficacy. With low insecticide efficacy of 70%, initiate strategies always perform better than the guide strategies (figure 2.12). When insecticide efficacy improves to 90% (figure 2.7), guide strategies start to show superiority under some combinations of trapping efficiency and threshold (i.e., trapping efficiency between 0.3 and 0.5 with the threshold of $y_t = 3$ flies per acre, and trapping efficiency greater than 0.5 with the threshold of $y_t = 5$ flies per acre). When insecticide efficacy further improves to 97%, the cost advantages of the guide strategy become even more compelling (figure 2.13). These results suggest that improvement in insecticide efficacy will result in the dominance of the guide strategy, which is more desirable environmentally.



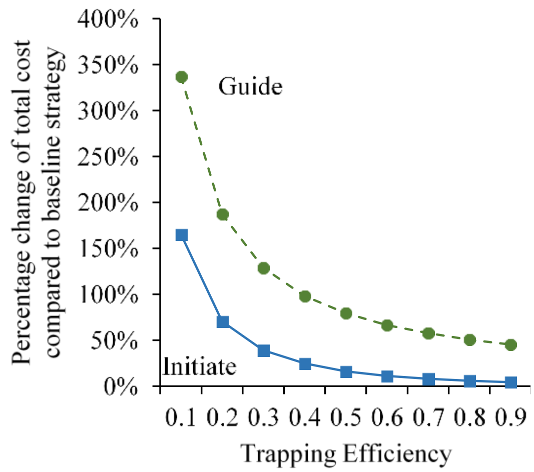
(a) Threshold = 1 fly per acre



(b) Threshold = 3 flies per acre

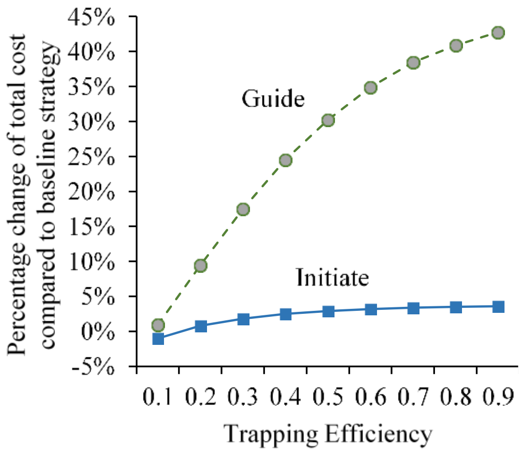


(c) Threshold = 5 flies per acre

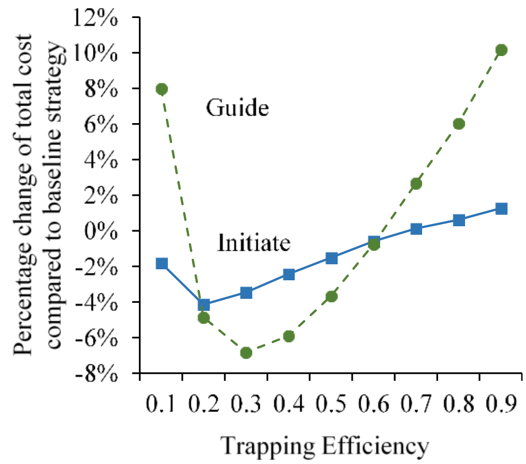


(d) Threshold = 10 flies per acre

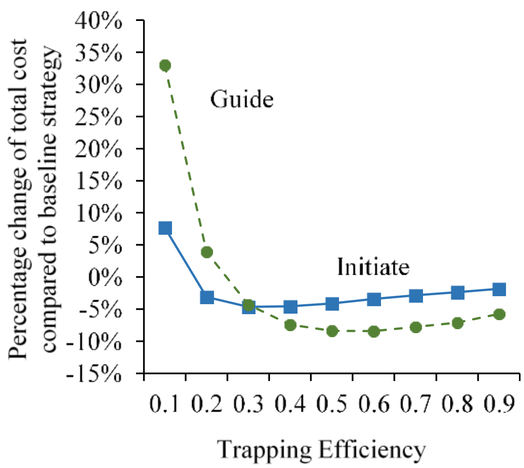
Figure 2.12. Monitor-to-initiate strategy vs. monitor-to-guide strategy: low efficacy insecticide (70%)



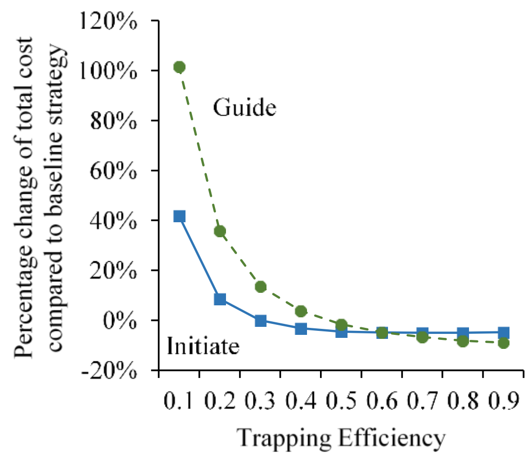
(a) Threshold = 1 fly per acre



(b) Threshold = 3 flies per acre



(c) Threshold = 5 flies per acre



(d) Threshold = 10 flies per acre

Figure 2.13. Monitor-to-initiate strategy vs. monitor-to-guide strategy: ultra-high efficacy insecticide (97%)

2.5 Conclusion

In this paper, we developed a dynamic bioeconomic model to identify cost-minimizing SWD management strategies. We employed a Bayesian state-space model to simultaneously account for uncertainties of SWD population dynamics in both the state transitioning process and the observation process. We then calibrated the model to evaluate the performance of 10 alternative management strategies which consist of different combinations of monitoring and spraying actions. We found that the economic impact of different SWD control strategies depends on the efficiency of monitoring traps, the action threshold selected, and the efficacy of the insecticide. Our results show that including monitoring of the SWD population can help reduce insecticide use. Moreover, strategies which include monitoring can be both economically and environmentally superior to the spray-only strategy, when an appropriate action threshold is chosen. Our sensitivity analysis indicates that initiate strategies perform better than guide strategies when insecticide efficacy is low. However, guide strategies are preferred if insecticide efficacy improves.

Our findings are valuable to fruit growers, extension personnel and other stakeholders in advancing their SWD management practices. Nevertheless, our model has several limitations that should be addressed in future research. First, our model can be extended to examine a multi-year problem to account for possible SWD resistance due to insecticide overuse (Hueth and Regev 1974). For example, future research can model insecticide resistance as a “public bad” (Lazarus and Dixon 1984), and conversely, insecticide susceptibility as a “public good”. Individual growers have no incentive to conserve SWD susceptibility since they cannot control the insecticide application decisions of their neighbors. Socially, it will likely be optimal for growers to collectively use less insecticide to conserve susceptibility over many years. Second, our model only uses SWD monitoring data from a single farm and ignores the fact that SWD moves freely through space. The probabilities of SWD being caught may depend on the location of the monitoring traps and therefore a single farm’s data cannot provide coherent estimation of SWD population density (Royle and Young 2008). Future research should also account for SWD diffusion across regions and describe the SWD infestation within a “spatial-dynamic” problem (Epanchin-Niell and Wilen 2015; Atallah, Gómez, and Conrad 2017).

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CHAPTER 3

EXAMINING SPATIAL EFFICIENCY OF THE UNITED STATES FRESH VEGETABLE MARKET: THE CASE OF BROCCOLI EXPANSION ON THE EAST COAST

3.1 Introduction

Over the last several decades, United States (U.S.) fresh fruit and vegetable production has become increasingly concentrated in California. According to the 2014 California Agricultural Statistical Overview, California harvested 47% of the U.S. fresh vegetables, produced 52% of the national production and 60% of the value (CDFA 2015). This geographic concentration can be explained by California's climatic advantages that allow fresh vegetable production year-round. Although the year-round availability is beneficial to consumers, the long distance between production and demand locations may cause market inefficiencies (Goletti, Ahmed, and Farid 1995; Goodwin and Schroeder 1991).

Fresh vegetables produced in California need to travel over thousands of miles to their East Coast destination markets (Weber and Matthews 2008). A significant downside of the long distance transportation is high transaction costs, an important source of market inefficiency (Barrett 2001). The primary transaction cost incurred when marketing fresh produce is information costs. As distance between shipping and demand locations increases, the cost of obtaining information on market conditions also increases while the quality and quantity of information declines. In addition, the time-lag associated with long distance transportation makes it hard to communicate demand conditions back to packer-shippers, thus possibly creating a mismatch between demand and supply. Other types of transaction cost include bargaining costs and enforcement costs. These transaction costs make coordinating shipments difficult and lead to market inefficiencies. For example, both weather factors and possible loss in quality and quantity of fresh vegetables are causing shippers to adjust shipments from California to the East Coast and thus creating period shortages and gluts (Cook 2011; Sexton, Kling, and Carman 1991).

As concerns about concentration of fresh vegetable production in California grow, there is increased interest in expanding fresh vegetable production base across different geographic and climatic zones on the East Coast (Atallah, Gómez, and Björkman 2014; Krueger et al. 2002). Such geographic diversification can reduce transaction costs due to proximity to demand locations and increased regional self-reliance in fresh vegetable supply. Increased competition between packer-shippers nationwide might also be expected, thus making movement of fresh vegetables from source to market more efficient. Shifting production locations seasonally (i.e. winter production in Florida, summer in Maine, and other states in between during spring and fall) may allow the East Coast region to supply fresh vegetables year-round. Such geographic diversification requires plant varieties that adapt well to eastern growing conditions, new investments in post-harvest infrastructure, and modified supply chain networks to efficiently distribute fresh vegetables.

An additional important dimension of these efforts are the implications for performance of fresh vegetable market, in particular regarding spatial market efficiency. Measuring spatial market efficiency, which refers to the degree to which the zero marginal benefit equilibrium condition is satisfied (Barrett 2001; Fackler and Goodwin 2001), is a common approach to evaluate market performance (Faminow and Benson 1990). By examining spatial price linkages, the level of market efficiency provides evidence of market competitiveness, product flow efficiency, and pricing efficiency (Buccola 1983; Fackler and Goodwin 2001; Sexton, Kling, and Carman 1991).

In this paper, we examine the spatial efficiency of the U.S. fresh broccoli sector. Broccoli is a major specialty crop with well-known nutritional benefits and a farm gate value of $896 million (USDA-NASS 2014). Although consumed nationwide, broccoli is mainly produced in California, with about 90% of total production (Strange et al. 2010). California is able to supply broccoli year-round because of its favorable climate and other agronomic conditions. Broccoli is also planted in many eastern states but is available only seasonally, depending on the production location. Atallah, Gómez, and Björkman (2014) estimate that the East Coast market share of broccoli is about 2-5 percent in the spring-winter season and about 11% in the summer-fall season.

Broccoli produced in California requires long distance transport to reach East Coast demand locations. This may have several disadvantages. First, product quality is affected due to the relative high respiration rate of broccoli. Research shows that content of various health-promoting compounds in broccoli decreases in long distance transportation (Rodrigues and Rosa 1999). In addition, liquid ice is required when shipping broccoli long distances. This can create problems when shipping broccoli in a mixed load because melting ice can damage other products, thus compounding the difficulty of coordinating broccoli shipments to East Coast markets. The disadvantages of long distance transportation, together with growing consumer demand for regional foods, are increasing stakeholders' (including plant breeders, growers and marketers) interest in expanding broccoli production on the East Coast.

We investigate these prospects with a switching regime model to assess the spatial efficiency of the U.S. broccoli market. We assembled a database of weekly broccoli prices at selected shipping point and demand locations spanning the period

2008-2013. Using these data, we estimate market efficiency levels between California, the dominant broccoli supplier, and various wholesale terminal markets. To further test whether or not production competition from East Coast influences market efficiency, we compared market efficiency levels for different seasons when broccoli is available in East Coast supply locations.

Our results suggest that broccoli production on the East Coast might contribute to improved market efficiency. This finding provides evidence of benefits accruing to the expansion of the eastern broccoli industry. Our model can help estimate the magnitude of transaction costs. Stakeholders can incorporate those estimates into decisions on whether or not to join the expansion of the East Coast broccoli market. Our results might also be relevant to other vegetable commodities (e.g. carrots, celery, endive, lettuce) produced primarily in California at present but with potential for expansion on the East Coast.

3.2 Literature Review

In spatially efficient markets, marginal profits from arbitrage should equal zero (Barrett 2001; Fackler and Goodwin 2001). The level of spatial market efficiency has been widely used to measure market performance in various dimensions (Faminow and Benson 1990). That is, measures of spatial market efficiency can indicate whether agricultural products are distributed efficiently or whether misallocation in the distribution system (i.e., periods of gluts or shortages) exists (Sexton, Kling, and Carman 1991). A number of empirical studies have measured spatial market efficiency for agricultural products using a variety of models and econometric methods (Fackler and Goodwin 2001). Fackler and Tastan (2008) provide a comprehensive summary of this literature. Most studies focused on storable commodities (e.g., rice, maize, wheat, soybeans and coffee) or livestock products (e.g., cattle and hogs). For example, Baulch

(1994) examined spatial market efficiency of rice markets in the Philippines; Faminow and Benson (1990) evaluated the Canadian hog market; Goodwin and Schroeder (1991) tested the U.S. cattle market; Moser, Barrett, and Minten (2009) examined Madagascar's rice market; Brosig et al. (2011) analyzed the Turkish wheat market; and Lee and Gómez (2013) investigated the international coffee market. Only a few paper studied the fresh produce markets. Among them, Sexton, Kling and Carman (1991) tested the U.S. celery markets; Susanto, Rosson and Adcock (2008) investigated the North American onion markets; and Santeramo (2015) analyzed European fresh vegetables markets.

The literature shows two primary frameworks to examine spatial market efficiency (Myers, Sexton, and Tomek 2010). The first is the co-integration/error correction model (ECM) pioneered by Ravallion (1986), which has been used in many studies (e.g., Goodwin and Piggott 2001; Myers 2013; Yang and Leatham 1998). In general, ECMs are appropriate to evaluate spatial efficiency when price series data are non-stationary and co-integrated (Goodwin and Piggott 2001; Meyer 2004). The second framework is the switching regime model, which was first applied to spatial efficiency of agricultural commodities by Sexton, Kling and Carman (1991), and subsequently extended by Baulch (1997), Barrett and Li (2002), Negassa and Myers (2007) and Butler and Moser (2010), among others. The switching regime model is appropriate to estimate spatial efficiency when production is concentrated in few locations and consumption occurs in multiple locations (Sexton, Kling, and Carman 1991). One advantage of switching regime model is one's ability to estimate the probability that a given market falls in one of three regimes, namely efficient arbitrage, gluts or shortages. Therefore, choosing the most appropriate framework to assess spatial market efficiency depends on the research objectives as well as the characteristics of the market and the data.

Agricultural markets typically exhibit seasonality in production, and in turn, seasonal price patterns. Ignoring such seasonality may lead to biased market efficiency assessments (Zanias 1999), particularly for highly perishable products such as fresh vegetables, including broccoli. A few studies have taken seasonality into account when measuring spatial market efficiency in grain markets (e.g., Myers 2013; Zanias 1999). However, seasonality has been largely ignored in the literature focusing on vegetable markets. One notable exception is Sexton, Kling and Carman (1991), which studied the degree of spatial efficiency in the U.S. fresh celery market for different production seasons.

The study reported here contributes to the spatial market efficiency assessment literature in several ways. Given the characteristics of the market, and after verifying that broccoli price series are not co-integrated, we built on Sexton, Kling and Carman (1991) to develop a switching regime model and examine the level of spatial market efficiency for U.S. broccoli market. Our study takes into account the influence of production seasonality on the level of spatial market efficiency. In addition, we compare the degree of spatial market efficiency in West Coast and East Coast demand locations, which supported the negative influence of distance on spatial market efficiency found by Goodwin and Schroeder (1991) and Goletti Ahmed, and Farid (1995). Finally, our model can help estimate the magnitude of transaction costs, which can be used by stakeholders to decide whether or not to join the expansion of broccoli production on the East Coast.

3.3 Empirical Methods

We use a switching regime model following Sexton, Kling and Carman (1991) to assess the extent of market efficiency of the U.S. fresh broccoli market. The key premise of the model is that there are three regimes between a shipping point and a demand location: (a) an efficient arbitrage regime, (b) a shortage regime, or (c) a glut regime, depending on whether the price differences between the demand locations and shipping points equal, exceed or fall below the corresponding transaction costs. The probabilities of the three market regimes are estimated as parameters which can be used to assess the level of market efficiency.

Denote p_{it}^{S} as the price in the shipping point *i* in time *t* and p_{jt}^{D} as the price in the demand location j ($j = 1, 2, 3, \dots, n$) in time t. In addition, let τ_{ijt} denote the transaction cost between the shipping point i and demand location j at time t. Transaction costs are defined to include transport expenses and other unobserved costs associated with the exchange. Following Sexton, Kling and Carman (1991), we assume that the transaction cost τ_{ijt} is a random variable with constant mean T_{ij} and has the following distribution:

(1) $$\tau_{ijt} = T_{ij} + v_{ijt}, v_{ijt} \sim N\left(0, \sigma_{ijv}^{2}\right),$$

where v_{ijt} is the error term, *N* is the normal distribution, and σ_{ijv}^{2} is the variance of transaction cost in the market pair *(i, j)*. According to the law of one price, if markets are efficient (or fully integrated), then the following condition holds for each shipping point *i* at a given time period t:

(2) $$p_{it}^{S} = p_{1t}^{D} - \tau_{i1t} = p_{2t}^{D} - \tau_{i2t} = \cdots = p_{nt}^{D} - \tau_{int}$$

However, if there are product distribution misallocations due to factors such as shipment lags, imperfect information and risk factors (Buccola 1983), then markets are deemed inefficient, setting the stage for periodic gluts or shortages of product at a given demand location *j*. In these cases, the equalities in Equation (2) will not hold for every t.

To examine the existence of periodic gluts and shortages, we define the price difference between shipping point i and demand location *j* as $R_{ijt} = p_{jt}^{D} - p_{it}^{S}$. Assume that the data generating process for R_{ijt} (we drop the subscript i and j for simplicity) is as follows:

(3) $R_t = T + v_t + u_t, \ with\ probability\ \theta_1,$

(4) $R_t = T + v_t - u_t, \ with\ probability\ \theta_2,$

(5) $R_t = T + v_t, \qquad with\ probrobability\ 1 - \theta_1 - \theta_2,$

where u_t is a one-side, positive half-normal random variable with variance σ_u^2 and is independent of v_t. In this representation of R_t, Equation (3) identifies a regime of product shortages at demand locations; Equation (4) defines a regime of product gluts at demand locations; and Equation (5) defines a regime of efficient arbitrage (i.e., efficiency of markets or market spatial efficiency). Using the density of the sum of a normal random variable and a truncated normal random variable (Nelson 1964), we can write the density functions for R_t in each of the three regimes as follows:

(6) $$f_{1t} = \left[\frac{2}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\varphi\left[\frac{R_t-T}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\left[1-\Phi\left[\frac{-(R_t-T)\sigma_u/\sigma_v}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\right],$$

(7) $$f_{2t} = \left[\frac{2}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\varphi\left[\frac{R_t-T}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\left[1-\Phi\left[\frac{(R_t-T)\sigma_u/\sigma_v}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\right],$$

(8) $$f_{3t} = \frac{1}{\sigma_v}\varphi\left[\frac{R_t-T}{\sigma_v}\right],$$

where $\varphi(\cdot)$ is the standard normal density function, and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

We use maximum likelihood estimation (MLE) to estimate this model. The likelihood function can be formulated as follows:

(9) $$L = \prod_{t=1}^{T}[\theta_1 f_{1t} + \theta_2 f_{2t} + (1-\theta_1-\theta_2)f_{3t}]$$

The unobserved transaction cost T, the probabilities for the shortages and gluts regimes θ_1 and θ_2, and the error parameters σ_v^2 and σ_u^2 can be estimated by maximizing the log of Equation (9). The probability for the efficient arbitrage regime can be subsequently calculated from the estimates of θ_1 and θ_2. The estimated parameters can indicate whether periodic product gluts or product shortages occur in various demand locations. Furthermore, to take seasonality into account, we separately estimate probabilities for the three regimes for the winter-spring season and for the summer-fall season. By doing so, we can test whether the market efficiency levels for the season when there is regional production in the demand location differs significantly from the season when there is no supply on the East Coast.

Figure 3.1. Shipping point and demand locations

3.4 Data and Descriptive Statistics

We use weekly broccoli prices for both shipping points and demand locations from the Agricultural Marketing Service of the U.S. Department of Agriculture (USDA-AMS 2013), covering the period from June 1, 2008 to May 31, 2013. The shipping point data is from Santa Maria, California which is a major broccoli producing area with shipments of fresh broccoli to the East Coast year-round (Strange et al. 2010). For demand locations, we employ terminal market prices for all seven major eastern U.S. cities reported by USDA-AMS: Boston, New York, Philadelphia, Baltimore, Columbia (South Carolina), Atlanta, and Miami. For comparison purposes, we also include two western cities, Los Angeles and Seattle, in our analysis. These cities are grouped as locations in the West, Northeast and Southeast of the U.S. (see figure 3.1).

Table 3.1. Summary statistics for weekly broccoli price data

Markets	**N**	**Mean Price**[a]	**Standard Deviation**
Shipping point			
Santa Maria	260	10.24	4.16
Terminal markets			
West			
Los Angeles	260	14.30	4.52
Seattle	260	17.07	5.34
Northeast			
Boston	253	16.20	4.34
New York	233	16.67	4.23
Philadelphia	259	15.77	4.02
Baltimore	236	17.04	3.75
Southeast			
Columbia	236	19.18	3.97
Atlanta	259	18.64	4.67
Miami	238	18.78	3.85

a: Unit: dollar per 20 lb carton.

Table 3.1 shows the summary statistics for broccoli price data for the shipping point and the demand locations. Price units are dollars per 20-lb carton of fresh broccoli crowns. As expected, the shipping point, Santa Maria, has the lowest broccoli mean price of $10.24 per carton. Prices for demand locations are generally higher than that of the shipping point but vary depending on their respective distance to the shipping point. Los Angeles, the closest demand location to Santa Maria, has the lowest terminal price of $14.3 per carton. Cities located in the Northeast have higher mean prices, between $15.77 and $17.04 per carton, but lower than Columbia, Atlanta and Miami in the Southeast, which have the highest mean prices of $19.18, $18.64 and $18.78 per carton respectively. Table 3.1 also shows that all locations experience volatile broccoli prices and have comparable standard deviations that varied between $3.75 and $5.34 per carton over the study period.

To take seasonality into account in our analysis and test whether production competition from East Coast impacts market efficiency, we organized the data into two subsets: summer-fall (June to November) and winter-spring (December to May). The summary statistics for the separated data are reported in table 3.2. For Santa Maria, the shipping point, the mean price for the winter-spring season is $10.62 per carton, which is $0.76 higher than the summer-fall average price. This pattern holds for most demand locations located in the West and in Southeast as well. In contrast, there are no significant price differences between the winter-spring and summer-fall seasons for all northeastern cities. The reason could be that, while lower summer-fall shipping prices are transmitted to these demand location, they are offset by higher transportation costs in the summer-fall season (USDA-AMS 2014). The standard deviation of prices for Santa Maria in the winter-spring season is $4.55 per carton, which is also higher than the summer-fall season. This higher volatility in prices at the shipping point in the winter-spring season appears to be transmitted to all demand locations where, on average, there is a deviation of $4.87 in terminal prices, compared with $3.60 during the summer-fall season.

Table 3.2. Summary statistics for separated weekly broccoli price data

Markets	Winter-Spring			Summer-Fall		
	N	Mean price	Standard deviation	N	Mean price	Standard deviation
Shipping point						
Santa Maria	130	10.62	4.55	130	9.86	3.70
Terminal						
West						
Los Angeles	130	15.10	5.01	130	13.49	3.82
Seattle	130	18.04	6.27	130	16.09	3.99
Northeast						
Boston	128	16.29	4.99	125	16.11	3.56
New York	113	16.41	4.69	120	16.90	3.76
Philadelphia	129	15.75	4.79	130	15.78	3.10
Baltimore	109	16.68	3.89	127	17.35	3.62
Southeast						
Columbia	114	19.58	4.68	122	18.80	3.13
Atlanta	129	19.03	5.43	130	18.24	3.73
Miami	108	18.55	4.06	130	18.97	3.66

3.5 Results

We first report the parameter estimates from Equation (9) before seasonality is taken into account (table 3.3). The estimated probabilities of gluts, shortages and efficient arbitrage allows the level of market efficiency between Santa Maria and each demand location to be assessed. These results are in line with expectations. That is, broccoli

Table 3.3. ***Parameter estimates for spatial market efficiency in U.S. fresh broccoli markets***

Markets	T Transaction Cost[a]	σ_u^2	σ_v^2	θ_1 Shortage	θ_2 Glut	$1-\theta_1-\theta_2$ Efficient	Log likelihood	N	T as % of mean price
West									
Los Angeles	3.62	8.82	1.66	0.20	0.02	0.78	-510	260	25%
	(23.20)[b]	(2.57)	(5.23)	(2.26)	(0.88)				
Seattle	5.79	41.40	9.82	0.22	0.02	0.76	-738	260	34%
	(12.46)	(2.42)	(4.83)	(1.84)	(0.83)				
Northeast									
Boston	6.64	11.18	1.08	0.20	0.46	0.34	-610	253	41%
	(23.60)	(5.57)	(2.32)	(3.72)	(4.65)				
New York	7.01	17.65	3.20	0.11	0.34	0.55	-592	233	42%
	(19.73)	(4.30)	(3.22)	(2.13)	(2.87)				
Philadelphia	7.27	12.06	0.63	0.08	0.70	0.22	-604	259	46%
	(22.25)	(8.16)	(2.00)	(3.20)	(6.38)				
Baltimore	7.12	8.37	1.74	0.27	0.30	0.44	-548	236	42%
	(21.02)	(4.26)	(2.14)	(2.35)	(2.60)				
Southeast									
Columbia	9.49	19.17	2.70	0.20	0.34	0.46	-623	236	50%
	(26.52)	(4.34)	(2.61)	(3.13)	(3.17)				
Atlanta	8.13	12.93	3.01	0.19	0.11	0.70	-604	259	44%
	(31.91)	(1.97)	(3.64)	(1.52)	(1.59)				
Miami	9.95	15.07	1.18	0.19	0.59	0.23	-617	238	53%
	(21.42)	(7.40)	(1.74)	(3.83)	(4.74)				

a: Unit: dollar per 20 lb carton.
b: t-value in parentless.

shipments from Santa Maria to western cities (i.e. Los Angeles and Seattle) operate primarily under an efficient arbitrage regime. Specifically, the probabilities of efficient arbitrage for Los Angeles and Seattle are 78% and 76%, respectively.

In contrast, shipments to the majority of eastern cities exhibit a higher probability of market inefficiencies (i.e., gluts or shortages) than their western counterparts. For example, the probabilities that markets are efficient between Santa Maria and Boston, New York, Philadelphia, Baltimore, Columbia (South Carolina) and Miami are only 34%, 55%, 22%, 44%, 23% and 46%, respectively. It is also interesting to note that, for these markets, the estimated probabilities of gluts (θ_2) are all higher than the estimated probabilities of shortages (θ_1). These results suggest that Santa Maria often ships excess broccoli to these demand locations. The only exception is Atlanta, which exhibits a high probability of efficient arbitrage (70%).

The estimated transaction costs (dominated by transportation expenses) are in line with expectations and tend to increase with the distance to the shipping point. Miami has the highest estimated transaction cost ($9.95 per carton), while Los Angeles has the lowest transaction cost ($3.62 per carton). It is important to note that, as expected, transaction costs account for a significant portion of demand location prices located on the East Coast, ranging from 41% to 53% of terminal point prices. In addition, northeastern demand locations exhibit transaction costs that are lower than those of their southern counterparts even though they are located farther away from Santa Maria.

The above discussion suggests that there is a higher probability of market inefficiencies between Santa Maria and eastern U.S demand locations relative to their western counterparts. An important related question is whether or not competition from East Coast producers can improve market efficiency. To shed light on this question and to incorporate seasonality in our analysis, we examined differences in efficiency levels between seasons (winter-spring and summer-fall). Parameter estimates from Equation (9), by season, are shown in table 3.4. Results suggest that shipments from Santa Maria to western demand locations operate under an efficient regime during both the winter-spring season and the summer-fall season. The efficiency levels for Seattle for the two seasons are both 78%. And the efficiency levels for Los Angeles for the two seasons are virtually identical at 79% and 80%, respectively.

In contrast, our results suggest that market efficiency levels for these two seasons differ significantly in eastern demand locations. For demand locations in the Northeast, the probability of efficient arbitrage is lower in the winter-spring season (ranging from 3% in Philadelphia to 45% in New York) when broccoli is not produced in this region. Conversely, in the summer-fall season, when broccoli is in production in the northeast, the probability of efficient arbitrage is much higher, ranging from 43% in Boston to 87% in New York.

The results for southeastern demand locations are reversed compared to those for the northeastern demand locations (table 3.4). In Atlanta, the market is more efficient in the winter-spring season (67%) when there is broccoli available from growers in Georgia and Florida. On the other hand, our results suggest that the probability of efficient arbitrage is equal to zero in the summer-fall season for the Atlanta market. The Miami market is an exception. The efficiency levels for Miami are the same (28%) for both seasons. However, the estimates for the probabilities of shortage regime and glut regime are not statistically significant for the winter-spring season, which may indicate a much higher probability of an efficient regime. This result supports the hypothesis that southeastern demand locations are more efficient in the winter-spring season, when regional supplies of broccoli are available. The results are different for Columbia (South Carolina). Even though this city is close to Atlanta,

Table 3.4. Seasonal parameter estimates for spatial market efficiency in U.S. fresh broccoli markets

Markets	Season[a]	T	σ_u^2	σ_v^2	θ_1 Shortage	θ_2 Glut	$1-\theta_1-\theta_2$ Efficient	Log likelihood	N	T as % of mean price
West										
Los Angeles	Winter	4.16	11.43	2.40	0.16	0.04	0.79	-277	130	28%
		(13.31)	(0.75)	(2.68)	(0.79)	(0.56)				
	Summer	3.31	3.97	1.12	0.20	0.00	0.80	-218	130	25%
		(12.52)	(0.90)	(2.29)	(0.73)	(0.00)				
Seattle	Winter	6.43	47.58	15.74	0.20	0.02	0.78	-391	130	36%
		(6.27)	(0.93)	(2.65)	(0.73)	(0.32)				
	Summer	5.28	28.18	6.27	0.22	0.00	0.78	-337	130	33%
		(9.85)	(1.59)	(2.35)	(1.31)	(0.00)				
Northeast										
Boston	Winter	6.66	12.93	1.00	0.21	0.57	0.22	-325	128	41%
		(11.46)	(4.62)	(1.20)	(2.72)	(3.34)				
	Summer	6.66	8.42	1.09	0.20	0.37	0.43	-280	125	41%
		(19.75)	(2.97)	(1.80)	(2.26)	(2.53)				
New York	Winter	6.89	18.97	2.75	0.09	0.46	0.45	-292	113	42%
		(11.38)	(3.35)	(1.98)	(1.45)	(2.48)				
	Summer	6.77	28.45	5.27	0.08	0.05	0.87	-295	120	40%
		(22.21)	(0.81)	(3.33)	(0.84)	(0.56)				

a: "Winter" here stands for "Winter-Spring" and "Summer" here stands for "Summer-Fall".

Table 3.4. Seasonal parameter estimates for spatial market efficiency in U.S. fresh broccoli markets (continued)

Markets	Season	T	σ_u^2	σ_v^2	θ_1 (Shortage)	θ_2 (Glut)	$1-\theta_1-\theta_2$ (Efficient)	Log likelihood	N	T as % of mean price
Northeast(continued)										
Philadelphia	Winter	8.14	17.53	0.03	0.05	0.92	0.03	-307	129	52%
		(29.83)	(6.56)	(0.63)	(2.48)	(13.14)				
	Summer	6.81	10.31	0.97	0.11	0.44	0.46	-288	130	43%
		(24.77)	(4.29)	(2.50)	(2.23)	(3.53)				
Baltimore	Winter	5.54	8.67	0.18	0.63	0.26	0.11	-258	109	33%
		(15.31)	(5.81)	(0.85)	(5.47)	(3.99)				
	Summer	7.35	10.43	1.41	0.23	0.17	0.60	-279	127	42%
		(31.89)	(2.94)	(2.70)	(2.35)	(2.28)				
Southeast										
Columbia	Winter	8.74	22.77	4.77	0.30	0.27	0.43	-322	114	45%
		(10.52)	(2.36)	(1.42)	(1.51)	(1.70)				
	Summer	9.55	15.54	2.25	0.14	0.27	0.59	-294	122	51%
		(28.87)	(2.38)	(2.53)	(2.21)	(1.91)				
Atlanta	Winter	7.52	15.43	4.90	0.31	0.02	0.67	-322	129	40%
		(8.74)	(1.22)	(2.06)	(0.82)	(0.27)				
	Summer	10.28	7.52	0.55	0.05	0.95	0.00	-273	130	56%
		(8.17)	(3.42)	(1.05)	(0.92)	(2.18)				
Miami	Winter	9.60	6.94	10.56	0.00	0.72	0.28	-293	108	52%
		(0.16)	(0.05)	(0.14)	(0.00)	(0.03)				
	Summer	10.06	12.55	0.83	0.18	0.53	0.28	-319	130	53%
		(27.15)	(6.22)	(1.72)	(3.04)	(4.47)				

our estimates indicate that the probabilities of efficient arbitrage in the winter-spring and summer-fall seasons are 43% and 59%, respectively. This may be due to the fact that North Carolina and South Carolina are able to supply broccoli to Columbia (South Carolina) during the fall months.

Our analysis of the influence of seasonality on market efficiency reveals other important aspects of the broccoli market on the East Coast. For example, we found that the probability of a glut regime tends to be higher than the probability of a shortage regime when regional supply is not available. This implies that Santa Maria may ship excess broccoli to these markets during the seasons when there is no regional production. Our results also indicate that transaction costs are not consistently higher in the summer-fall season even though the USDA reports higher truck rates during these months (USDA-AMS 2014). For example, the estimated transaction cost for Philadelphia in winter-spring season is $8.14 per carton, which is higher than the transactions cost in the summer-fall season for that market ($6.81 per carton). In addition, for Boston and New York, there are no seasonal differences in estimated transaction costs. These results imply that, during the winter-spring season, other components of the transaction cost (e.g., communication cost, information cost associated with price and quality discovery, and storage costs) may offset the lower truck rates.

Overall, these results suggest that markets on the East Coast tend to be more efficient during the seasons when regional product is available. Consequently, our findings support the hypothesis that, in the case of fresh market broccoli, diversification of supply locations via an expansion of production on the East Coast may contribute to improved market efficiency.

3.6 Conclusion

In this article, we employed a switching regime model to examine the spatial market efficiency of the U.S. fresh broccoli market. We used the parameter estimates derived from this model to calculate the probabilities that a given market operates under three alternative regimes, namely efficient arbitrage, gluts and shortages. Specifically, we assessed market efficiency levels of broccoli markets between the main U.S. shipping location (Santa Maria, California) and various western and East Coast demand locations. We also examined differences in market efficiency levels between the summer-fall season and the winter-spring season.

We find that the seasons when regional supply is available coincide with higher probabilities of having efficient markets. Our results indicate that broccoli shipments from Santa Maria to western demand locations tend to operate primarily under efficient regimes (e.g. efficient arbitrage), regardless of the season. In contrast, shipments to the majority of East Coast demand locations exhibit higher probability of operating under glut or shortage regimes. In addition, our results indicate that markets tend to be more efficient in the summer-fall season in the Northeast region, whereas southeastern cities tend to exhibit higher probabilities of efficient arbitrage in the winter-spring season.

These findings suggest that East Coast markets may be more efficient when there is regional competition due to broccoli production on the East Coast. Consequently, expanding broccoli production on the East Coast may improve overall market efficiency. These findings provide support to current efforts to develop broccoli varieties adapted to East Coast growing conditions and to extend the harvest seasons in this region.

Our study provides useful insights to the market performance of the U.S. broccoli markets but also highlights several limitations that warrant future research.

First, like most spatial analysis studies, price is the only variable that we use in this investigation. Future research should incorporate data on shipment volumes and focus on structural models to identify sources of market inefficiency. Second, we utilized wholesale prices at terminal markets reported by USDA but broccoli, like other vegetable crops, is increasingly being shipped directly to self-distributing retailers that operate regionally and even nationally. Most of these retailers have developed their own supply chain structures. The prices they pay to packer-shippers may not correspond exactly to the terminal prices reported to USDA. Consequently, efforts to incorporate syndicated data[1] (e.g., IRI scanner data) in market efficiency analyses show promise in the future. Finally, our econometric model assumes that transaction costs are constant over the study period. Future research should develop statistical tests (using longer price data series) to test the validity of this assumption.

[1] Syndicated data can be structured or unstructured data that is primarily provided by external sources (data providers) as a result of their analysis and studies conducted. For example: Marketing results, Survey results, Common usage patterns and forecasting information.

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CHAPTER 4

WILLINGNESS TO PAY, QUALITY PERCEPTION, AND LOCAL FOODS: THE CASE OF BROCCOLI

4.1 Introduction

Locally-grown is increasingly becoming an important characteristic consumers consider when making food purchasing decisions. Consumers often perceive locally-produced food to have higher-quality with superior attributes such as freshness and flavor. Local foods are also associated with such benefits as reduced environmental impacts and stronger local economies (King, Gómez, and DiGiacomo 2010; Martinez et al. 2010). These perceived benefits may influence consumer willingness to pay (WTP) for local foods.

A large body of literature has studied consumer preferences and WTP for local foods in the United States (U.S.) (see Martinez et al. 2010 and Feldmann and Hamm 2015 for detailed overviews). Most studies find that consumers are willing to pay a price premium for local foods. However, these studies implicitly assume that consumers perceive that local foods have superior quality than non-local foods. Little is known about WTP for local foods taking into account differences in consumer perception of food quality between local and non-local foods. In addition, extant literature has not examined the effect of information about origin on consumer perceptions of quality, and how these perceptions are related to consumer WTP. Studying these issues can help famers and supply chain channel members develop superior strategies for marketing local foods.

In this article, we study consumer WTP and quality perceptions of local broccoli grown in New York State (NYS) in comparison to product grown in

California. The broccoli sector is an excellent setting for studying such issues. Broccoli, like many U.S. fresh fruits and vegetables, are produced mainly in California (USDA NASS 2017), whereas the majority of the demand occurs in the East Coast of the country. However, potential water shortages in California, higher transportation and handling costs, and increasing consumer demand for local food have encouraged industry stakeholders to increase broccoli production in the East Coast, including NYS (Atallah, Gómez, and Björkman 2015). Moreover, increasing broccoli production (similar to other fresh fruits and vegetables production) can potentially provide fresh product to East Coast consumers, lower supply chain transportation and handling costs, reduce environmental impact through lower carbon emissions, and promote growth within regional rural economies.

One challenge of growing broccoli in the East Coast is the lack of appropriate varieties suited to eastern growing conditions. Most broccoli consumed in the U.S. is harvested from varieties specifically developed for California production environments. The combination of warmth and humidity common in East Coast production regions creates deformities and often prevents high-quality head formation (Griffiths et al. 2012). Consequently, researchers are developing new broccoli varieties better adapted to eastern agro-ecological conditions. One marketing strategy is to increase East Coast broccoli varieties' competitiveness by promoting them as "locally-grown". But before adopting this strategy, stakeholders need to be informed of the influence of the "locally-grown" attribute on consumer WTP and the perception of quality. Only by understanding these issues stakeholders can capitalize from potential price premiums that consumers are willing to pay for local food.

We run an economic experiment with non-student subjects to assess the effect of information about origin on consumers' WTP and perceptions of the appearance and taste of the three broccoli varieties (one commercial variety grown in California, and two new varieties developed for NYS growing conditions and produced in this state). Appearance and taste are two of the most important quality attributes considered by consumers when making purchasing decisions. We employ a Tobit model[2] to study the effect of information about origin on consumer WTP to account for the truncated nature of the data. Additionally, we use random effects model to examine the influence of information about origin on consumer perception of product appearance and taste. Our results show that consumers evaluate both the appearance and the taste of the two local broccoli varieties lower than the California variety when information about origin is not provided. However, consumers' evaluations of the two local broccoli varieties improves substantially when they are given information about origin. Results also indicate that consumers are willing to pay for a price premium for the two NYS-grown varieties.

Our results provide evidence that information about origin has a positive effect on both consumer WTP and quality perception. Our results shed light on appropriate marketing strategies for the two newly developed local broccoli varieties. Our results are relevant for other U.S. fruit and vegetable commodities (e.g. carrots, celery, endive and lettuce, among others) produced primarily in California but which have the potential to be produced in the East Coast.

4.2 Literature Review

As consumers' interest in local food is growing steadily, so is the number of studies on topics and issues related to local foods (see Martinez et al. 2010 for an overview). However, there is not a universally accepted definition of "local food" (Martinez et al.

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[2] The Tobit model is designed to estimate linear relationships between variables when the dependent variable is truncated (i.e., there is either left- or right-censoring in the dependent variable).

2010). Definitions of local food are usually based on one or more of the following features or characteristics: geographic proximity (DePhelps et al. 2005; Hu et al. 2012), political boundaries (e.g. Washington apples, Idaho potatoes, California Peaches, and Florida Citrus) (Zepeda and Leviten-Reid 2004), how local food is retailed (e.g. farmers market, community supported agriculture, etc.), and length of the supply chain (Marsden et al. 2000), among others. In this paper, we adopt the political boundary definition, which is "grown and available for purchase within a State's borders" (Martinez et al. 2010). This definition is also the most popular among the top 10 grocery retailers (Martinez et al. 2010). In this paper, we use the term "New York Grown" to represent "locally-grown".

Most local food studies focus on consumer preferences and WTP for local products. Martinez et al. (2010) summarizes a series of studies on WTP for a wide range of locally-produced food in the U.S. Not surprisingly, they find that consumers are willing to pay higher prices for local foods. A number of studies examine the effect of multiple factors that influence consumer preferences and WTP for local food, including quality perception (Brown 2003; Carpio and Isengildina-Massa 2009), nutritional reasons (Eastwood, Brooker, and Gray 1999; Loureiro and Hine 2002), better value for the price (Wolf, Spittler, and Ahern 2005), support for environment and local economy (Darby et al. 2008), and demographic characteristics (Brown 2003). Other studies analyze how the values of "local" and "organic" interact and influence consumer WTP (James, Rickard, and Rossman 2009; Yue and Tong 2009; Roosen, Kottl, and Hasselbach 2012).

Several methods have been used by researchers to study consumer preferences and WTP for local food. Earlier studies tend to use the hypothetical approaches such as personal interviews as well as online, mail and telephone surveys (Eastwood 1996; Brown 2003; Zepeda and Leviten-Reid 2004). In a hypothetical survey, respondents answer WTP questions where the payment of the stated WTP is hypothetical. These studies have been criticized for not being incentive-compatible to reveal the real consumer WTP (Wertenbroch and Skiera 2002). In recent years, experimental auctions have become increasingly popular to investigate the impact of labeling on WTP for food attributes (Dickinson and Bailey 2002; Umberger et al. 2002; Lusk, Feldkamp, and Schroeder 2004). Real money and real products are exchanged in an experimental setting so that participants have a greater incentive to reveal their true value for a product than in a hypothetical survey setting (Lusk 2003; Lusk, Feldkamp, and Schroeder 2004). For example, Grebitus, Lusk and Nayga (2013) uses second-price auctions to study the effect of distance of transportation on consumer WTP for local food. Similarly, Shi, House and Gao (2013) uses a Becker-DeGroot-Marschak (BDM) auction to determine in what way purchase intentions affect WTP for organic and locally grown blueberries. Other methods studying consumer preferences and WTP for local food include conjoint analysis (Darby et al. 2008) and choice experiments (Alfnes et al. 2006; Yue and Tong 2009).

In this paper, we employ BDM auctions of broccoli to study the effects of information about origin on 1) consumer WTP and 2) consumer perception of product quality. In a BDM auction, subjects submit sealed bids for a good. A random price is then drawn from a predetermined distribution. Individuals with bids greater than the randomly-drawn price “win” the auction and purchase a unit of the good at that randomly-drawn price. Because the bids of respondents do not determine the purchase price, the BDM auction creates an optimal environment for rational respondents to reveal their actual WTP (Becker, DeGroot, and Marschak 1964; Lusk and Shogren 2007).

Our paper is related to a stream of literature which studies the effect of country-of-origin (COO) on consumer WTP and perception of product quality.

According to Elliott and Cameron (1994), consumer attitudes about local and non-local products are similar to the effect of COO, which has long been discussed in the literature. Newman et al. (2014) provides an overview of research related to COO labeling and implications for food marketing systems. This literature generally agrees that consumers tend to perceive domestic food to be of superior quality than imported food products (Umberger 2005; Lobb and Mazzocchi 2007; Pouta et al. 2010). Consumer WTP for COO information have also been widely researched by marketing and consumer behavior literature. For example, Lim et al. (2013) studies U.S. consumer preference and WTP for COO-labeled beef steak and food safety enhancements. In many cases, consumers' higher WTP for domestic food is associated with their perceptions of superior quality (Dickinson and Bailey 2002; Umberger et al. 2002). Loureiro and Umberger (2003) find that consumer are willing to pay an average of $1.53 and $0.70 per pound more for steak and hamburger labeled as "U.S. Certified".

Despite the importance of quality perception in deciding consumer preference and WTP for local food (Durham, King, and Roheim 2009), little has been done to examine the effect of information about origin on consumer perceptions of local food quality and how do these perceptions relate to consumer WTP, which is the focus of this study. One exception is Stefani, Romano and Cavicchi (2006), who studies the impact of alternative definitions of the region of origin on consumer WTP and consumer evaluation of food quality. Another paper that is closely related to our work is Bi et al. (2012), who uses experimental auctions to study the effect of sensory attributes (viewing, peeling, and tasting) on consumer WTP for two new tangerine varieties. They find that consumers change their WTP based on the different attributes of the tangerines and that internal fruit attributes (e.g., flavor, juiciness, ease of peeling) are more important to consumers than external attributes (e.g., appearance).

4.3 Experimental Design

We ran an economic experiment with nonstudent subjects to examine consumer WTP for three broccoli varieties: a commercial variety from California (from here on referred to as "California variety") and two newly developed NYS grown varieties (from here on referred to as "NYS 1" and "NYS 2") that are undergoing field trials before being launched to market. The California variety was bought from a local grocery store and had dark green, firm, uniform and domed head. The two NYS varieties were harvested from an Agricultural Experiment Station where the field trial for the new broccoli varieties was conducted. NYS 1 had a light green color, flat, and non-uniform head. NYS 2 was designed by researchers to have very similar appearance to the California variety. To maintain similar post-harvest product attributes, we stored the two NYS varieties in the same way the California variety stored. To ensure similar product broccoli quality across experimental sessions, all three broccoli varieties were kept on ice to maintain quality.

We collected WTP information from subjects who were exposed to one of two treatments regarding the origin of the three broccoli varieties. In the first treatment, subjects did not receive information regarding the origin of the varieties. They revealed their WTP for the three varieties solely based on their evaluations of the appearance and the taste of the three broccoli varieties. In the second treatment, subjects were told that the two NYS varieties were grown in New York State and the third variety in California.

Subjects were recruited through a local experimental economics research laboratory's email system. They were seated randomly at individual computer terminals with privacy shields, were informed that all decisions they made would be kept strictly confidential, and were given $25 for participating and might have the opportunity to actually purchase broccoli. A maximum of 24 computer terminals were available per session, and the number of subjects in each session ranged from 15 to 24. After signing a consent form, subjects were given a brief introduction of the experiment, which included the amount of money they would earn and the rules of the experiment. We began each session with two practice rounds to demonstrate how the BDM auction would be conducted. In the practice round, subjects submitted bids for a dollar bill and a chocolate bar so they would become familiar with the bidding process of the auctions. At the beginning of the broccoli auction, lab assistants first displayed one crown (approximately one pound) of each of the three broccoli varieties used in the experiment so that subjects could examine the broccolis' appearance closely. Subjects were given a small sample of each broccoli variety to taste and were then asked to rate the scores of the appearance and taste of each variety from 1 to 9, with 9 being most favorable.

After observing the appearance and having tasted the three broccoli varieties, subjects were asked to place bids for one pound of each variety in the auction. Each subject submitted bids between $0.00 and $5.00 for one pound of each variety. The BDM auction method was used to elicit maximum WTP for the broccoli varieties. Although subjects bid for all three varieties, they were informed that only one of the three auctions would result in an actual transaction. After bids for all auctions were submitted, one out of the three auctions was randomly chosen to be actually binding. In this case, the subjects who won their bids for the randomly selected auction would be “required” to purchase one pound of broccoli at the market price, which is to be deducted from their participation endowment. After the auctions, subjects completed a computerized survey asking demographic and purchasing habit information, including gender, age, education, income, cooking frequency, broccoli consumption in their meals and whether the subject was the primary shopper in the household (please see Appendix for the survey used in the experiments).

4.4 Data and Empirical Model

We collected 240 observations from 80 non-student subjects in the broccoli tasting experiment sessions. Figure 4.1 shows descriptive statistics of demographic information about experiment subjects based on responses to questions in the survey. The figure indicates that 72.5% of the subjects in our sample are female. The age of these subjects ranges from under 20 years to 70-74 years old. 28.8% of the subjects received a 4-year college degree and 23.8% of them received a Master Degree. The annual income of the subjects range from less than $20,000 to more than $90,000. 27.5% of subjects cook their meals 4-5 times a week and 41.3% cook their meals more than 5 times a week. 53.2% of the subjects include broccoli in their meals 1-3 times a week. On average, 82.3% of the subjects are primary shopper in their households.

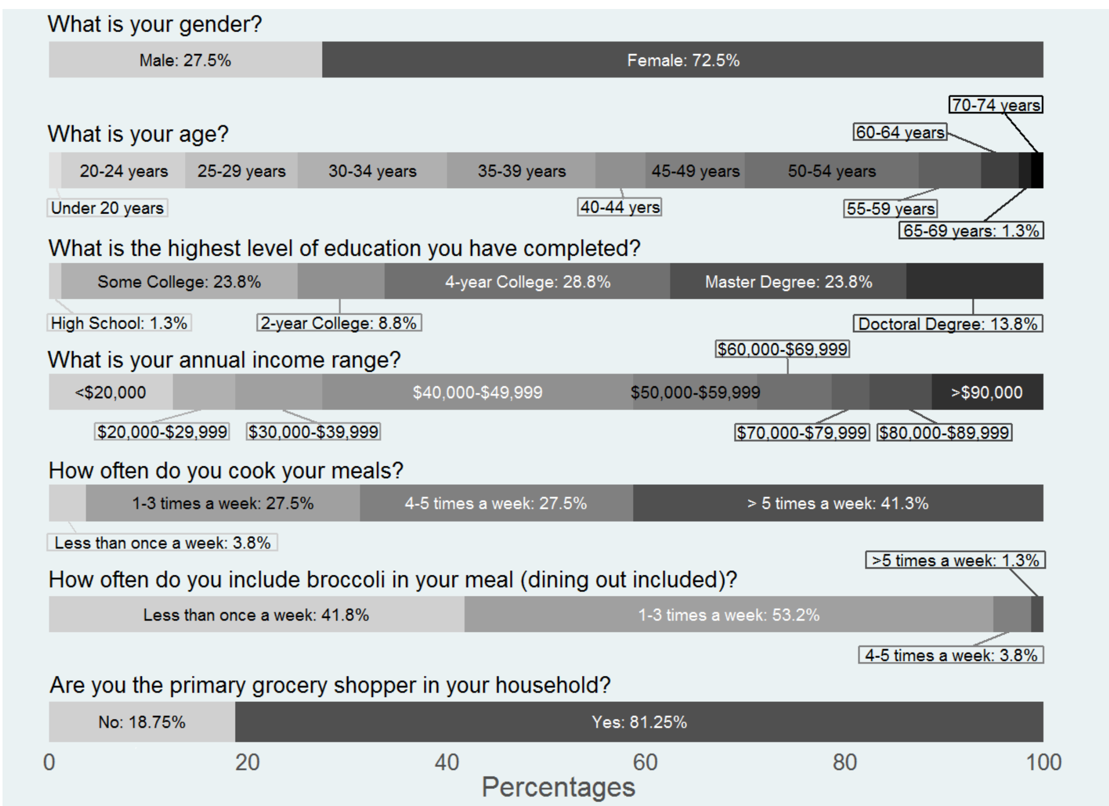

Figure 4.1. Demographic Characteristics of Subjects

Table 4.1. Summary Statistics for WTP, Score of Appearance and Taste

	Obs.	WTP ($/lbs.)	Appeara nce	Taste
Overall	**240**	**1.6 (0.82)**	**6.47 (2.04)**	**6.76 (1.87)**
No Information	**123**	**1.53 (0.89)**	**6.21 (2.18)**	**6.39 (2.03)**
California	41	1.62 (0.91)	7.83 (1.22)	6.68 (1.91)
NYS 1	41	1.44 (0.88)	4.22 (1.82)	6.10 (2.12)
NYS 2	41	1.52 (0.89)	6.59 (1.66)	6.4 (2.05)
Information	**117**	**1.68 (0.74)**	**6.74 (1.85)**	**7.13 (1.62)**
California	39	1.62 (0.73)	8.00 (1.17)	6.59 (1.55)
NYS 1	39	1.7 (0.75)	5.82 (1.55)	7.21 (1.76)
NYS 2	39	1.71 (0.75)	6.38 (2.01)	7.59 (1.39)

* Standard deviation in parentheses.

Table 4.1 provides subjects' average WTP and their evaluation scores of the appearance and taste of the three broccoli varieties, by origin information treatment. Forty-one subjects participated in the "no information" sessions, while 39 subjects participated in the sessions with information about product origin. The table shows that the average WTP for all 80 subjects is $1.64 per pound of broccoli, which is comparable to retail prices in local supermarkets. For the no information treatment, the average WTP is $1.53, which is slightly lower than the average WTP for the whole sample. When subjects are informed about the origin of the product, the mean WTP become $1.68, which is slightly higher than the average WTP for the whole sample. Subjects' evaluation scores of appearance and taste in the two treatment groups follow a similar pattern.

A simple comparison of the descriptive statistics among the three broccoli varieties within each treatment group reveals intriguing information. For the no information treatment, subjects' average WTP for the California variety is $1.62, while their WTP for the NYS 1 and NYS 2 are much lower, $1.44 and $1.52 respectively. Meanwhile, the average score of appearance for the NYS 1 is 4.22, which is much lower than the score for the California variety (7.83). For the NYS 2, the difference in the scores for both appearance and taste are modest relative to the California variety. The average score of appearance for the NYS 2 is 6.59, which is 1.24 lower than the California variety, and the average score of taste for NYS 2 is 6.4, which is 0.28 lower than the California variety.

In contrast, subject's evaluations of WTP and appearance are substantially different in the information treatment, in comparison to the no information treatment. First, both the WTP and the taste for the two NYS varieties become higher than for the California variety (recall they were lower for the no information treatment). Interestingly, evaluation of the appearance of the two NYS varieties in the information treatment group (5.82 and 6.38) are lower than for the California variety (8.00), which is similar to the no information treatment. In addition, although evaluations of the appearance and taste of NYS 2 (6.38 and 7.59) are both higher than those of NYS 1 (5.82 and 7.21), the WTP for them is practically the same ($1.70 and $1.71).

When comparing data between the two treatment groups (information and no information), the descriptive statistics suggest that subjects' WTP as well as evaluation of appearance and taste of the California variety are very close. For example, subjects' WTP for the California variety in the two treatment groups are both

$1.62, and their score of appearance is only slightly higher when given information about origin (8.00) compared to when they are not provided information (7.83). In contrast, WTP and evaluation of appearance and taste of the two NYS varieties are all markedly higher in the information treatment than in the no information treatment. The only exception is that the appearance evaluation score for NYS 2 in the information treatment (6.38) is slightly lower than that of the no information treatment (6.59).

To test whether subjects' WTP are affected by the provided origin information, we run two random-effects models. We first run a simple Ordinary Least Squares (OLS) random effects model with and without demographic variables. We also run a Tobit model to account for the censored nature of the WTP data. The Tobit model has been widely used by agricultural economists to study consumer WTP for attributes of food products (e.g. Bernard and Bernard 2009; Kanter, Messer, and Kaiser 2009). The latent value of individual i's WTP for variety j, denoted as WTP_{ij}^*, is expressed as a function of the variety V_j, the dummy variable I to indicate whether subject receive origin information treatment, and the subjects' demographic characteristics, X_i. Because individuals submitted bids for different broccolis in the experiment, we employ a random effects Tobit model to account for the panel nature of the data. The parameter, ν_i, is an individual-specific disturbance for subject i, and ε_{ij} is the error term which is assumed to follow a normal distribution with mean zero and standard deviation σ. In Equation (1), we assume a linear functional form for the WTP equation. The relationship between the observed variable WTP_{ij} and the latent variable WTP_{ij}^* is shown in Equation (2). If we assume the observed WTP_{ij} and the latent WTP_{ij}^*, to be the same, then Equation 1 collapses to the OLS random-effects model.

(1) $$WTP_{ij}^* = \alpha + \beta_j V_j + \gamma I + \delta_j V_j I + \theta X_i + \nu_i + \varepsilon_{ij}^{WTP}$$

(2) $WTP_{ij} = max\{0, WTP_{ij}^{*}\}$

In the model specified above, α is the WTP for one pound of the California variety when no information about the origin of the three types of broccoli are revealed, β_j captures the price premium that consumers are willing to pay for the NYS variety j (relative to the California variety) when the origin information is not provided, γ is the effect of information about origin on consumer's WTP for the California variety, δ_j describes the interaction effects between varieties and origin information treatment, which captures the effect of information about origin on the price premium that consumers are willing to pay for the NYS variety j (relative to the California variety), and θ is a vector of parameters of consumer characteristics.

We run a similar OLS random effects model to examine how subjects' perceptions of the quality (appearance and taste) of the three broccoli types is affected by the information about origin. To do so, we change the dependent variable in the Equation (1) to subjects' score of the appearance and taste of the three broccoli types. The new OLS models for the effect of information about origin on subject's perception of the appearance and taste of the three broccoli types are as follows:

(3) $Appearance_{ij} = \alpha + \beta_j V_j + \gamma I + \delta_j V_j I + \theta X_i + v_i + \varepsilon_{ij}^{Appearance}$

(4) $Taste_{ij} = \alpha + \beta_j V_j + \gamma I + \delta_j V_j I + \theta X_i + v_i + \varepsilon_{ij}^{Taste}$

4.5 Results and Discussion

In this section, we present the estimation results from the OLS and Tobit models specified above, using the data collected in our experiments. Table 4.2 presents the estimated parameters from the random effects OLS and Tobit models in Equation 1 and Equation 2. Given that the results from the OLS model are very close to those from the Tobit model, from here on we only discuss the results from the Tobit model with demographic variables.

Table 4.2. Willingness to Pay Estimates Using Random-effects Tobit and OLS Models

Explanatory Variables	**OLS Model**		**Tobit Model**	
Intercept	1.621*** (0.000)	1.997*** (0.000)	1.610*** (0.000)	1.994*** (0.000)
Variety				
NYS 1	-0.181 (0.100)	-0.185 (0.105)	-0.180 (0.105)	-0.182 (0.110)
NYS 2	-0.098 (0.188)	-0.100 (0.195)	-0.103 (0.179)	-0.104 (0.149)
Origin Information	-0.001 (0.997)	-0.071 (0.681)	0.010 (0.956)	-0.071 (0.688)
Interaction terms				
Origin Information × NYS 1	0.258* (0.050)	0.263* (0.054)	0.257** (0.043)	0.259* (0.058)
Origin Information × NYS 2	0.193* (0.088)	0.195* (0.093)	0.198* (0.079)	0.199* (0.072)
Demographic				
Gender		0.104 (0.586)		0.105 (0.604)
Age		0.030 (0.305)		0.030 (0.382)
Education		-0.067 (0.294)		-0.066 (0.324)
Income		0.041 (0.467)		0.041 (0.476)
Cooking Frequency		-0.043 (0.755)		-0.045 (0.762)
Broccoli in Meal		-0.115 (0.400)		-0.113 (0.451)
Primary Shopper		-0.042 (0.877)		-0.042 (0.886)

* p-values in parentheses (* p<0.1, ** p<0.05, *** p<0.01).

The estimated intercept in the first row of table 4.2 is $1.994 per pound, which describes consumers' willingness to pay for the California variety without knowing its origin. The estimated WTP is comparable to the retail price of commercial Californian broccoli in grocery stores. The next two rows describe the premium consumers are willing to pay for the two NYS varieties (relative to the California variety), when no information about their origin is revealed. The results suggest that consumers are willing to pay $0.182 and $0.104 less per pound for the two NYS varieties relative to the California variety. These two estimates are not significant at 10% significant level. The next row shows the estimated difference in WTP for the California variety in the no information treatment and from the information treatment (i.e., the group received origin information of the three broccoli varieties). The estimated coefficients for the interaction terms for the two NYS varieties are $0.259 and $0.199 per pound, respectively and both are statistically significant at the 1% level. These are the price premium consumers are willing to pay when they are told the two NYS varieties are NYS grown. The last seven rows show the impacts of demographic variable and purchasing habit on consumers' WTP for the broccoli varieties included in our experiment. None of the estimated coefficients for the demographic variables is significant, which means that consumers' WTP are not affected by their socioeconomic or demographic characteristics.

We show the effect of information about origin on consumers' perceptions of appearance and taste of the three broccoli types in table 4.3. To better summarize the relationship between the effects of information about origin on appearance and taste, and WTP, we also include WTP results from the Tobit random effects model (demographic information included) in table 4.3.

The estimated intercept with appearance score as the dependent variable is 7.772. This means that consumers in the no information treatment give the California

Table 4.3. Comparison of the Effect of Origin Information on WTP, Appearance and Taste

Explanatory Variables	**WTP**	**Appearance**	**Taste**
Intercept	1.994*** (0.000)	7.772*** (0.000)	6.829*** (0.000)
Variety			
NYS 1	-0.182 (0.110)	-3.725*** (0.000)	-0.590 (0.155)
NYS 2	-0.104 (0.149)	-1.250*** (0.000)	-0.282 (0.437)
Origin Information	-0.071 (0.688)	0.189 (0.486)	0.028 (0.943)
Interaction terms			
Origin Information × NYS 1	0.259* (0.058)	1.546*** (0.000)	1.205** (0.025)
Origin Information × NYS 2	0.199* (0.072)	-0.365 (0.491)	1.282*** (0.008)
Demographic			
Gender	0.105 (0.604)	0.438** (0.037)	0.808*** (0.004)
Age	0.030 (0.382)	-0.005 (0.914)	-0.350 (0.545)
Education	-0.066 (0.324)	0.010 (0.889)	-0.017 (0.857)
Income	0.041 (0.476)	0.047 (0.347)	0.148*** (0.009)
Cooking Frequency	-0.045 (0.762)	-0.230** (0.048)	-0.313*** (0.006)
Broccoli in Meal	-0.113 (0.451)	0.274* (0.081)	0.315 (0.141)
Primary Shopper	-0.042 (0.886)	-0.320 (0.187)	-0.845*** (0.001)

* p-values in parentheses (* p<0.1, ** p<0.05, *** p<0.01).

variety an average score of 7.772. The two estimated coefficients under the subheading *Variety* (NYS 1 and NYS 2) are -3.725 and -1.250, respectively. This suggests that consumers in the no information treatment evaluate the appearance of the two NYS varieties lower than the California variety by simply observing the appearance of the three broccoli types, without knowing the origin. The estimated coefficient of *Information* is not statistically significant, indicating that consumers in the no information treatment and the information treatment give the same score for the appearance of the California variety. The estimated coefficient for the interaction term *Origin Information* $\times$ *NYS 1* is 1.546. That is, when consumers are told this variety is grown in NYS, their appearance score for this variety is higher by 1.546 points than the California variety. We do not find the same effect for NYS 2 (the coefficient is not statistically significant). One possible reason is that this variety was bred to have similar appearance to the California variety. Consumers already give a high score for the appearance of this variety, and consequently telling them that it is grown in NYS does not change their perception of appearance. Variety NYS 1, on the other hand, looks quite different (light green color, and does not have a uniform dome like the California variety). Thus, when consumers are told that this variety is NYS-grown, they are more forgiven of the fact that it looks quite different to the commercial broccoli typically found in supermarkets.

Our results show that female subjects tend to rate the appearance of the broccoli 0.438 higher than male subjects. In addition, results suggest that the more often the subject cooks meals in the households, the more likely he/she rates the appearance of the broccoli lower (by 0.230 points). Additionally, and the more often a subject includes broccoli in his/her meal, the more likely the subject rates the appearance of the broccoli higher (by 0.274 points).

Table 4.3 also presents results of the factors influencing attribute taste scores. The results are substantially different from that for the attribute appearance. Subjects in the no information treatment give the California variety an average score of 6.829 in taste. The estimated coefficients of *NYS 1* and *NYS 2* are not statistically significant. This means that subjects in the no information treatment evaluate the taste of the two NYS varieties the same as the California variety. Similar to the results of appearance, the estimated coefficient of *Information* is not statistically significant, indicating that consumers in both no information and information treatments give the same score for taste to the three varieties. The estimated coefficients for the two interaction terms (*Origin Information* $\times$ *NYS 1* and *Origin Information* $\times$ *NYS 2*) are both statistically significant at the 5% level. This suggest that, when told the two NYS varieties are grown in NYS, consumers perceive the taste of these varieties higher by 1.205 and 1.282, respectively, in comparison to the California variety. Similar to the results for the appearance attribute, female subjects tend to rate broccoli's taste higher than male subjects. Income also has a positive impact on subject's rate of the taste. The more often the subject cooks, the lower this subject rates the taste of broccoli. Lastly, primary shoppers tend to rate the taste of broccoli 0.845 lower than non-primary shoppers.

When comparing the results in table 4.3, we find that the impact of information about origin on consumer's perception of product appearance and taste are related to the impact on the price premium they are willing to pay. In particular, for variety NYS 1, subjects' evaluations of appearance and taste are higher when information about origin is provided. At the same time, subjects are willing to pay a price premium of $0.259 for this variety when information about origin is provided. Considering variety NYS 2, results suggest that only consumer's evaluation of taste is higher when information about origin is provided. This increase in taste scores is consistent with the price premium of $0.199 that consumers are willing to pay for this variety. Taken together, these results indicate that although the impact of information about origin on WTP for NYS 1 is larger than for NYS 2, this does not necessarily mean consumers are willing to pay less for the latter: table 4.1 shows that consumers have almost the same WTP for the two NYS varieties in the information treatment.

4.6 Conclusion

Consumers place value on local foods for both social and product quality reasons. However, little research has been conducted examining the effects of information about origin on consumer WTP and quality perceptions, which is very important for vegetable marketing strategies. In this paper, we designed an economic experiment to examine consumer WTP and quality perception (i.e., product appearance and taste) of three broccoli varieties, one commercial variety from California and two new NYS-grown varieties that are undergoing field trials before being launched to market. In the experiment we assess how consumers' WTP for and perception of product quality are affected by information about origin (local versus non-local).

Experimental data on consumers' willingness to pay as well as evaluation of the appearance and the taste of the three broccoli varieties, demographic information and purchasing habits were collected from non-student subjects. In our analysis, we used a Tobit model to account for the censored nature of the WTP data. Our results show that when no information about origin is given, consumers are willing to pay more for the California variety relative to the two NYS varieties. Consumers also rate both the appearance and the taste of the California variety higher than the two NYS varieties when no information about product origin is provided. However, when consumers are told that the two NYS varieties are locally-grown, their perception of both the appearance and the taste of the two NYS varieties (relative to the California variety) increases, and their willingness to pay for the two NYS varieties also increases. The impact of information about origin on the price premium consumers are willing to pay for the two NYS varieties (relative to the California variety) are $0.259 and $0.199 per pound. These results indicate that although consumers may still prefer the California broccoli variety, they are willing to pay a price premium when the two new broccoli varieties were promoted as locally-grown.

These findings have two important policy implications. First, our results show that consumer perception of broccoli quality is affected by information about origin. Even if the quality of the NYS-grown broccoli varieties is rated lower than the quality of the California variety, consumers appear to be more forgiven when they are promoted as locally-grown. As perception of the quality of the local broccoli increases, consumer WTP for them increases as a result. Second, the positive price premium show that New York broccoli can benefit from the increased interests in local foods. Broccoli producers and channel members can use the estimated price premium from our paper as a reference when making their growing, pricing, or promotion decisions.

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CHAPTER 5

GENERAL CONCLUSION

The three chapters in this dissertation study a farm manager's optimal invasive species control decisions, the spatial efficiency of the U.S. broccoli market, and the effect of information about product origin on consumer WTP and quality perception. They show how wide the fields of agribusiness is, and how useful the results to stakeholders in the agribusiness sector are. Furthermore, this dissertation makes several contributions to the literature and have important policy implications.

The first chapter develops a Bayesian framework to optimally monitor and control an invasive species when the population size of the species can only be partially observed. The model developed in this chapter can be extended and applied to study other disease and pest management problems. In addition, this chapter contributes to the literature on the control of the SWD by providing an economic analysis to evaluate optimal SWD managing strategies. The findings from this chapter are valuable to fruit growers, extension professionals and other stakeholders in the fruit sector in advancing their SWD management practices.

The second chapter employs a switching regime model to examine the spatial market efficiency of the U.S. fresh broccoli market. The results of this chapter can provide useful insights to the market performance of the U.S. broccoli markets. The findings suggest that East Coast markets may be more efficient when there is regional competition from broccoli produced in the East Coast. Consequently, expanding broccoli production on the East Coast may improve overall market efficiency. These findings provide support to current efforts to develop broccoli varieties adapted to East Coast growing conditions and to extend the harvest seasons in this region. In addition, the model employed in this chapter can help estimate the magnitude of transaction costs. Stakeholders can incorporate those estimates into decisions on whether or not to contribute to the expansion of the East Coast broccoli market.

The findings from the third chapter have two important policy implications. First, the results show that consumer's perception of the quality of the broccoli is affected by information about origin. Even if the quality of the locally-grown broccoli varieties is rated lower than the quality of the California variety, consumers appear to be more forgiven about their quality when they are promoted as locally-grown. As perception of the quality of the local broccoli increases, consumer WTP for them increases as a result. Second, the positive price premium show that New York broccoli can benefit from the increased interests in local foods. Broccoli producers and channel members can use the estimated price premium from our paper as a reference when making their growing, pricing, or promotion decisions.

APPENDIX

Survey Questions for Experiment Conducted in Chapter 2:

1. What is your gender?

☐ Male ☐ Female

2. What is your age?

☐ Under 20 years	☐ 20-24 years	☐ 25-29 years
☐ 30-34 years	☐ 35-39 years	☐ 40-44 years
☐ 45-49 years	☐ 50-54 years	☐ 55-59 years
☐ 60-64 years	☐ 65-69 years	☐ 70-74 years
☐ 75-79 years	☐ 80 years or later	

3. What is the highest level of education you have completed?

☐ Less than High School	☐ High School/GED
☐ Some College	☐ 2-year College Degree
☐ 4-year College Degree	☐ Masters Degree
☐ Doctoral Degree	☐ Professional Degree (JD, MD)

4. What is your annual income range?

☐ Below $20,000	☐ $20,000-$29,999	☐ $30,000-$39,999
☐ $40,000-$49,999	☐ $50,000-$59,999	☐ $60,000-$69,999
☐ $60,000-$69,999	☐ $70,000-$79,999	☐ $80,000-$89,999
☐ $90,000 or more		

5. How often do you cook your meals?

☐ Never	☐ Less than once a week
☐ 1-3 times a week	☐ 4-5 times a week
☐ More than 5 times a week	

6. How often do you include broccoli in your meal (dining out included)?

☐ Never	☐ Less than once a week
☐ 1-3 times a week	☐ 4-5 times a week
☐ More than 5 times a week	

7. Are you the primary grocery shopper in your household?

☐ Yes ☐ No